

Review article

Neural dynamics of cognitive control: Current tensions and future promise

Dale Zhou^{a,b,c}, Danielle Cosme^{d,e,f}, Yoona Kang^{d,g}, Ovidia Stanoi^{d,e,f}, David M. Lydon-Staley^{d,h}, Peter J. Muchaⁱ, Emily B. Falk^{d,e,f}, Kevin N. Ochsner^j, Dani S. Bassett^{k,l,m,n,o,p}*

^a Department of Neurobiology and Behavior, University of California, Irvine, United States of America

^b Center for the Neurobiology of Learning and Memory, University of California, Irvine, United States of America

^c Department of Cognitive Sciences, University of California, Irvine, United States of America

^d Annenberg School for Communication, University of Pennsylvania, United States of America

^e Department of Psychology, University of Pennsylvania, United States of America

^f Marketing Department, Wharton School, University of Pennsylvania, United States of America

^g Rutgers, The State University of New Jersey, United States of America

^h Leonard Davis Institute of Health Economics, University of Pennsylvania, United States of America

ⁱ Department of Mathematics, Dartmouth College, United States of America

^j Department of Psychology, Columbia University, United States of America

^k Department of Bioengineering, School of Engineering and Applied Sciences, University of Pennsylvania, United States of America

^l Department of Physics & Astronomy, College of Arts and Sciences, University of Pennsylvania, United States of America

^m Department of Neurology, Perelman School of Medicine, University of Pennsylvania, United States of America

ⁿ Department of Electrical & Systems Engineering, School of Engineering and Applied Sciences, University of Pennsylvania, United States of America

^o Department of Psychiatry, Perelman School of Medicine, University of Pennsylvania, United States of America

^p Santa Fe Institute, United States of America

ARTICLE INFO

Keywords:

Network control theory
Network controllability
Dynamical systems theory
Self-regulation
Cybernetics
Network neuroscience
Connectome

ABSTRACT

Cognitive control is a suite of processes that helps individuals pursue goals despite resistance or uncertainty about what to do. Deficits of cognitive control underlie compulsive or risky behavior, as well as other clinical challenges associated with difficulties in regulating impulses, attention, thoughts, and feelings. Although cognitive control has been extensively studied as a dynamic feedback loop of perception, valuation, and action, it remains incompletely understood as a cohesive dynamic and distributed neural process. Here, we critically examine the history of and advances in the study of cognitive control, including how metaphors and cultural norms of power, morality, and rationality are intertwined with definitions of control, to consider holistically how different models explain which brain regions act as controllers. Controllers, the source of top-down signals, are typically localized in regions whose neural activations implement elementary component processes of control, including conflict monitoring and behavioral inhibition. Top-down signals from these regions guide the activation of other task-specific regions, biasing them towards task-specific activity patterns. A relatively new approach, network control theory, has roots in dynamical systems theory and systems engineering. This approach can mathematically show that controllers are regions with strongly nested and recurrent anatomical connectivity that efficiently propagate top-down signals, and precisely estimate the amount, location, and timing of signaling required to bias global activity to task-specific patterns. Importantly, the theory converges with established findings, provides new mathematical tools and intuitions for understanding control loops across levels of analysis, and naturally produces graded predictions of control across brain regions and modules of psychological function that have been unconsidered, marginalized, or indirectly linked. We describe how psychological and network control approaches converge and diverge, noting directions for future integration that could strengthen and sharpen our understanding and predictions of how the brain instantiates cognitive control.

Contents

1. Introduction	2
2. Cognitive control: Constructs and correspondence	4

* Corresponding author.

E-mail address: dani.bassett@yale.edu (D.S. Bassett).

<https://doi.org/10.1016/j.neubiorev.2026.106909>

Received 19 March 2026; Received in revised form 3 August 2026; Accepted 10 August 2026

Available online 17 August 2026

0149-7634/© 2026 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

3. Opportunities for expanding, formalizing, and integrating cognitive control constructs	15
Declaration of competing interest	17
Acknowledgments	17
Appendix	17
4.1. Fig. 1 methods	17
4.2. Fig. 2 methods	17
4.3. Fig. 3 methods	18
4.4. Fig. 5 methods	18
4.5. Fig. 6 methods	18
4.6. Citation diversity statement	18
References	19

1. Introduction

Meeting the demands of everyday life requires the ability to flexibly pursue all manner of goals, overcoming obstacles and resisting distractions along the way. In psychology, this ability is known as cognitive control, which is as crucial for single-minded striving toward one end as it is for flexibly changing aims (Carver and Scheier, 2001). Psychological definitions of control frame it as a suite of processes for prioritizing the pursuit of goals that may conflict with competing thoughts, emotions, impulses, motivations, desires, other goals, and behaviors. For example, cognitive control underlies the ability to inhibit responses that conflict with goals — representations of long-term and momentary outcomes — while also pursuing responses that align with them. To manage such conflicts, several subprocesses are thought to be involved, including conflict monitoring, cognitive flexibility, task switching, working memory, selective attention, inhibitory control, and learning (Monsell, 2003; Egner and Hirsch, 2005; Munakata et al., 2011; Miyake and Friedman, 2012; Jamadar et al., 2015; Braunstein et al., 2017; Friedman and Miyake, 2017; Eisenberg et al., 2019). Some goals, reached via habitual or automatic behaviors (e.g., thoroughly learned tasks), do not need cognitive control and using it to guide these behaviors would be counterproductive or an inefficient use of effortful control resources (Poldrack et al., 2005; Diamond, 2013; Neal et al., 2013; Amer et al., 2016; Bustamante et al., 2021). Pursuing some goals rather than others means weighing the value of allocating resources and time. Given that time is finite, as are the resources one can devote to control, this points towards the necessity of computing the value of exerting control (Yee and Braver, 2018; Shenhav et al., 2016; Stanovich, 2020; Touroutoglou et al., 2020). Once seen as a fatigable willpower akin to tired muscles (Ribot, 1911), control energy is now understood in terms of allocating mental resources including attention, working memory, motivation, and effort (Kool and Botvinick, 2018).

The importance of cognitive control is evident in its broad conceptual scope and applicability to a wide range of behavioral contexts, from the kitchen and cashier to the classroom, clinic, and courtroom, and even to one's own conscience. Conceptually, cognitive control is intertwined with broader behavioral constructs such as executive function, self-regulation, self-discipline, willpower, volition, delayed gratification, risk-taking, and emotion regulation (Fig. 1) (Duckworth and Kern, 2011; Mischel et al., 2011; Fujita, 2011; Diamond, 2013; Burman et al., 2015; Nigg, 2017; Inzlicht et al., 2021). Alterations in control function are hallmarks of many neurological and psychiatric conditions, contributing to distress and challenges to daily function related to loss of agency and autonomy (Arnsten and Rubia, 2012; McTeague et al., 2017; Barch et al., 2018; DeYoung and Krueger, 2018; Romer et al., 2021). Aspects of cognitive control have been analogized to a “moral muscle” related to a strength of will to resist temptations (Park et al., 2004; Duckworth et al., 2007; Hofmann et al., 2018; Wente et al., 2020; Speer et al., 2022), and research on the developmental trajectory of cognitive control has influenced legal standards for personal responsibility (Müller and Kerns, 2015; Luna, 2012; Luna and Wright, 2016). Finally, control is thought to have a causal

power over actions that paves the way for desired outcomes in school, health, finances, and criminal justice with consequences for individuals and societies (Duckworth and Seligman, 2005; Blair and Razza, 2007; Heatherton and Wagner, 2011; Moffitt et al., 2011; Mischel et al., 2011). These applications highlight a powerful normative worldview about cognitive control historically rooted in beliefs about power, morality, and rationality (Ribot, 1911; Gennara et al., 2023; Hofmann et al., 2018), which require critical reexamination (Lydon et al., 2014; Bermúdez and Murray, 2024).

Although much progress has been made towards characterizing cognitive control at multiple levels of analysis, many open questions remain. At present, working descriptions of cognitive control make different assumptions about what behaviors to focus on, the kinds of processes or representations involved, and how neural substrates instantiate control processes and representations. As such, questions remain about the goals and behaviors that exemplify “good” cognitive control, whether control processes and abilities are domain specific vs. domain general, and whether and how neural systems implement putative processes and mental representations. Varied and disparate working definitions of cognitive control represent major efforts from diverse perspectives to address these and related questions (Fig. 2) (Burman et al., 2015; Kotabe and Hofmann, 2015; Nigg, 2017; Milyavskaya et al., 2019; Eisenberg et al., 2019; Bunge, 2024).

Although psychologists mostly agree on what kinds of behaviors require cognitive control, conceptualizations of underlying processes still largely involve mapping individual component processes onto individual neural systems. This approach has identified various kinds of putative systems underlying control functions, such as working memory or conflict monitoring. However, this componential approach is difficult to reconcile with recent advances in computational, systems, and network neuroscience that emphasize parallel processing with dynamic and distributed representations. As such, current models of control can seem more akin to a chimeric list of behaviors and component parts rather than a coherent and holistic explanation of how complex behaviors emerge from control processes implemented by interacting neural systems.

By contrast, a neurobiological process account that highlights cognitive control as a distributed and dynamic network function could strengthen cohesion across levels of analysis (Eisenreich et al., 2017; Pessoa, 2023; Noble et al., 2023). A distributed account explicitly models the collective contribution of regions, including those not yet recognized by current paradigms. A dynamic account centers how control operates from moment-to-moment as a function of the evolution of collective activity, rather than only as a function of a terminal state where regions (co-)activate past a threshold. A network account models the brain as a complex system of units (nodes) interconnected by physical pathways (edges), and provides tools to formally quantify collective dynamics across too many regions to grasp without mathematical abstraction. At the intersection of distributed, dynamic, and network models is network control theory.

Similar to other major advances (Shenhav et al., 2013), the value of network control theory does not lie primarily in the novelty of its core components — nodes, edges, dynamics, and control targets — but in its explicit formalization of these elements in an interpretable

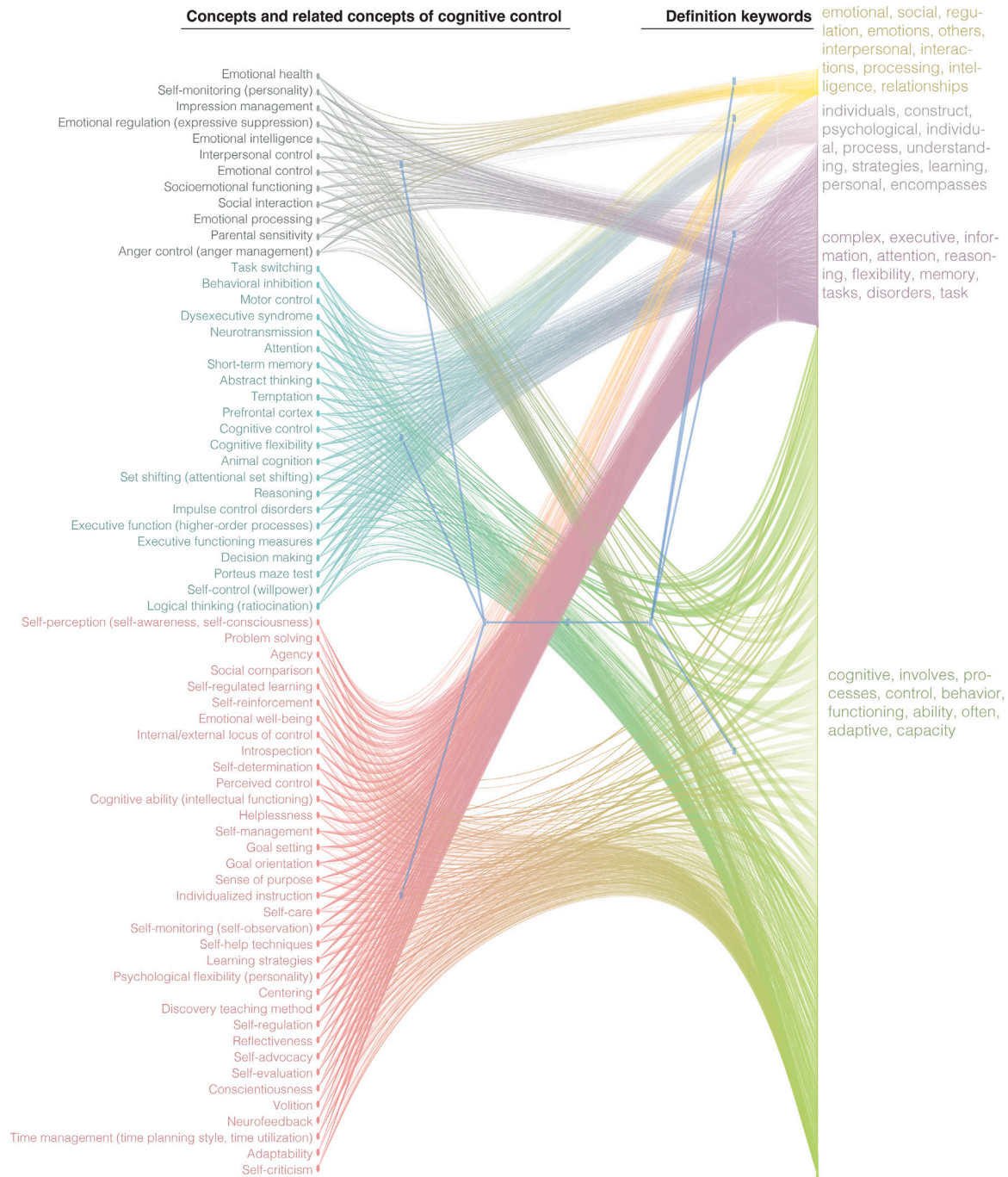


Fig. 1. Self-regulation concepts. Conflicting and fragmented working definitions of cognitive control remain a major challenge for developing cohesive theories, with many concepts used interchangeably despite continuous calls for clarity. Inconsistency is unavoidable as a force of scientific progress. In addition to pursuing more ecologically relevant tasks, clearer definitions, and consensus, understanding may come from embracing the plurality of basic scientific and applied goals across disciplinary boundaries. The American Psychological Association Thesaurus of Psychological Index Terms®. Provides concepts directly related to the concepts of “cognitive control” and “self-regulation”, as well as the terms’ definitions (American Psychological Association, 2023; Burman et al., 2015). Colors indicate groupings of the concept nodes based on community detection of the concept-by-keyword co-occurrence network (Gerlach et al., 2018). Concept nodes are directly or indirectly related to the “cognitive control” and “self-regulation” concepts, such as self-control, executive function, and agency. For the keyword nodes, we show the most frequent words within each group. Edges indicate co-occurrence. The blue tree network indicates hierarchical community structure, suggesting shared patterns of description across disciplines aiming to reduce and disentangle cognitive control and self-regulation into dynamically interacting components. The holistic, and admittedly unwieldy, backdrop of the varied kinds of concepts and functions detail the targets of explanation for a neurobiological process account that highlights cognitive control as a distributed and dynamic network function. See Appendix 4.1 for methodological details.

mathematical framework. This endeavor makes it possible to precisely characterize the kinds of control a brain region can exert over its activity toward both known and yet unknown control targets. Network control theory helps synthesize many key ideas in the neuroscience of

cognitive control in a precise and mathematically coherent account, linking the processes underlying regulation, development, hierarchy, and cost (Cohen et al., 1990; Desimone et al., 1995; Miller, 2000; Badre, 2008; Cole, 2017; Badre and Nee, 2018; Luna et al., 2015; Marek et al.,

2015; Crone and Steinbeis, 2017; Shenhav et al., 2013; Cools, 2015; Westbrook et al., 2020), while producing new predictions for unconsidered control components, processes, and targets. For example, network control theory advances understanding of cognitive control by identifying key brain regions and their development, predicting when and how much control is required, and extending insights across species. It improves behavioral and psychiatric prediction beyond simpler network metrics (e.g. the strength of a region's connectivity), and offers a framework for studying and modeling neurological and psychiatric (pharmacological, neurostimulation, psychological) interventions.

Goals of the review

Philosophers and scientists have theorized extensively about how people form goals, make decisions to support them, and flourish through attaining them. What constitutes a good life? Where do goals come from? How do we know if we are achieving them? Defining cognitive control becomes more difficult when both scientific and cultural frameworks constrain how we think about it, historically conflating control with willpower, relying on metaphors about social structures of power, and focusing on individual agency rather than collectives. When theories of cognitive control are shaped by the very social and psychological forces they aim to explain, the risk is that beliefs, values, and assumptions that have become second nature are embedded in our models of nature. How might we move beyond some of these assumptions and expand our ability to see how life actually works and as importantly how it could work? Taking a step back to describe how energy flows in the brain and moves people through decisions and actions with the mathematical language of network control theory offers new insight into how control works and how it might be leveraged to promote flourishing (Medaglia, 2019; Lynn and Bassett, 2019; Badre, 2020).

We first define key ideas across psychological and neuroscientific theories of cognitive control, and then highlight tensions which motivate a new conceptualization of cognitive control. For more detail on core psychological concepts, we point readers to literature on the psychology of goal pursuit and self-regulation (Fujita, 2011; Gollwitzer, 2013; Frese and Sabini, 2021; Inzlicht et al., 2021; Brandstätter and Bernecker, 2022), definitions of control effort (Inzlicht and Berkman, 2015; Westbrook and Braver, 2015; Thomson and Oppenheimer, 2022; Otto et al., 2025), computational models of cognitive control (Yee and Braver, 2023, 2020), syntheses of cognitive control across regions and units of analysis (Satpute et al., 2012; Egner, 2017; G. Gratton et al., 2018; Badre, 2022), the role of specialized brain regions (e.g., prefrontal cortex Miller, 2000; Friedman and Robbins, 2022; Menon and D'Esposito, 2022, dorsal anterior cingulate cortex Shenhav et al., 2013; Clairis and Lopez-Persem, 2023, and insular regions Menon and Uddin, 2010; Uddin, 2021) in allocating control (Silvestrini et al., 2023), component processes across cognitive control and executive function tasks (Miyake and Friedman, 2012; Niendam et al., 2012; Diamond, 2013; Friedman and Miyake, 2017; Jamadar et al., 2015), and the neurodevelopment of cognitive control (Somerville and Casey, 2010; Luna et al., 2010; Munakata et al., 2012; Luna et al., 2015; Crone and Steinbeis, 2017).

The next section conveys mathematical intuitions underlying network control theory, showing what is unique about the formulation with no assumption of prerequisite mathematical background. For more extensive mathematical treatments of the topic, see literatures on the general theory and applications (Motter, 2015; Liu and Barabási, 2016; D'Souza et al., 2023), applications to neuroscience (Tang and Bassett, 2018; Lynn and Bassett, 2019; Srivastava et al., 2020), didactic textbook chapters (Kim and Bassett, 2020; Bruntun and Kutz, 2022), practical tutorials and code (Karrer et al., 2020; Parkes et al., 2024), application to animal models including directed connectomes of *C. elegans* and mice (Towlson et al., 2018; Parkes et al., 2024), and applications to perturbing and predicting neural dynamics (Medaglia et al., 2017;

Shenoy and Kao, 2021; Srivastava et al., 2022). In the final section, we outline how each approach contributes to the other and potential future efforts to interdigitate the two constructs. When we refer to the psychological perspective of control, we use the term “cognitive control”, whereas we refer to the network science perspective, we use the term “network control”. When referring to the broader concept of self-regulation, we simply say “control”.

2. Cognitive control: Constructs and correspondence

The psychological construct of cognitive control

“If in general we class all springs of action as propensities on the one hand and ideals on the other, the sensualist never says of his behavior that it results from a victory over his ideals, but the moralist always speaks of his as a victory over his propensities. [...] And if a brief definition of ideal or moral action were required, none could be given which would better fit the appearances than this: It is action in the line of the greatest resistance”.

[— James, 1890]

Historical origins

Why would anyone act contrary to their own goals and ideals (Davidson, 2001)? It has long been recognized that achieving feats of self-control is difficult because different mental, emotional, and motivational processes conflict with one another. Plato conceptualized the mind as a team of horses representing passion and appetite controlled by a charioteer representing reason (Plato, 1952). Without the charioteer, the horses run wild and the mind cannot pursue virtuous purposes. Continuing in this contest between “dual processes”, the study of cognitive control has historically been framed as a conflict between uncontrolled and controlled aspects of the mind: automatic vs. deliberate; hot vs. cold; reactionary vs. willful; stimulus-driven vs. goal-driven; impulsive vs. inhibited; id vs. ego; distracted vs. attentive; off-task vs. on-task, and habitual vs. effortful. Such contests are frequently moralized as conflict between inner demons versus better angels, wherein the victory of virtues over vices drives human progress (Elias, 1939; Read et al., 1999; Pinker, 2012; Heckhausen, 2018; Hofmann et al., 2018).

Over a century ago, at the dawn of psychology, control was thought to tip the scales in these conflicts. This idea was captured by a simple yet enduring formula: cognitive control energy or effort E decides the balance between habitual instincts, impulses, motives, pleasures, and pains as propensities P and our ideals I (James, 1890). E is needed when $I < P$; that is, when habits override ideal goals. Cognitive control allows for $I + E > P$.

Recent advances

Although oversimplified, this basic formulation has been expanded or rearranged to explain many aspects of control behavior. E is not a unitary resource of will but a decomposable process with multiple elementary components (Nee et al., 2007; Nee and Jonides, 2008). E is partly about weighing the value of alternatives and monitoring progress (Miller et al., 1960; Daw et al., 2005; Kurzban et al., 2013; McGuire and Kable, 2013; Yee and Braver, 2023; Berkman et al., 2017; Yee and Braver, 2020; Lieder et al., 2018; Musslick and Cohen, 2021), a motivated and context-sensitive valuation of how to allocate time and let go of lost opportunities. This does not merely rebrand willpower as willingness to apply effort; this E is a subjective valuation that weighs the costs and benefits of I as contexts change, tracking when I promises greater reward, I is more probable, and reduced E can lead to better control outcomes (Padmala and Pessoa, 2011; Kool et al., 2017; Bustamante et al., 2021). E can also act as a divisor to P , rearranging the inequality to bring E to the other side as an inhibitory gate so that $I > \frac{P}{E}$ (Heatherton and Wagner, 2011; Munakata et al., 2011; Miyake and Friedman, 2012; Shenhav et al., 2013; Kotabe and Hofmann, 2015; Bunge, 2024). Other components amplify or diminish

E , such as emotions and motivations, and P is a function of many states and traits, such as risk taking, sensation seeking, and conscientiousness (Shackman et al., 2011; Zelazo and Carlson, 2012; Ochsner et al., 2012; Shenhav et al., 2013; Pessoa, 2017; Eisenberg et al., 2019; Enisman and Kleiman, 2024). Taken together, E is not a unitary input to tip the balance between (or among) habits and goals, but is a series of calculated choices shaped by separate but interacting component processes (Wood et al., 2022).

Component processes

Varied ideas have arisen across fields about the nature of these component processes (Figs. 2 and 3). Many psychologists view control as emerging from inhibition of automatic or goal-irrelevant responses, updating and monitoring working memory, and shifting attention between tasks (Miyake and Friedman, 2012; Diamond, 2013; Bunge, 2024). Cognitive psychologists view control processes as a function of learning to make reward-based decisions by applying selective attention and working memory to monitor and gate ongoing action when there is uncertainty about what to do until sustained or momentary goals are completed (Miller et al., 1960; Rougier et al., 2005; Daw et al., 2005; Koechlin and Summerfield, 2007; Yee and Braver, 2023; Braver, 2012; Botvinick and Cohen, 2014; Botvinick and Braver, 2015; Yee and Braver, 2020). Personality and social psychologists view control as the ability to regulate driving and restraining forces, supported by certain traits and feelings of autonomy, competence, and relatedness, in service of a rich hierarchy of personal goals of differing abstractness, generality, and duration (Deci and Ryan, 2000; Carver and Scheier, 1982; Duckworth et al., 2007; Duckworth and Kern, 2011; Kruglanski et al., 2012, 2015). Expectancy-value theorists in motivation psychology view control as driven by goals that have sufficient value balanced with confidence about the self-efficacy towards expected attainment in service to a system of needs and drives (Atkinson, 1957; Shah and Higgins, 1997; Feather, 1982; Lewin, 1936; Ryan et al., 2002; Heckhausen, 2018; Kruglanski et al., 2012). Neuroeconomists view control processes as a cost-benefit analysis in service of choice that maximizes benefits under costs of alternative opportunities, time, and mental resources (Glimcher and Fehr, 2013; Boureau et al., 2015; Kool et al., 2017; Berkman et al., 2017; Kool and Botvinick, 2018; Lieder et al., 2018).

Shared computations of dynamic feedback loops

Despite these differences, all consider the core control process as a dynamic feedback loop of perception, valuation, and action. This feedback loop describes cognitive control as a process balancing the choice to apply control effort with the value and efficacy of that effort, given the perception of the current situation. Choices influence what new sensory inputs, task stimuli, and options one attends to, and the “perception-action cycle” continues (Fuster, 1990; Ochsner and Gross, 2014; Botvinick and Cohen, 2014; Gross, 2015; Rmus et al., 2021). Over time, effective control is learning the range of actions that reduce the difference, or increase the congruency, between the expected value of choices and the perceived state of affairs (Miller et al., 2017; Carver and Scheier, 2001; Frömer et al., 2019; Bustamante et al., 2021; McDougale et al., 2022).

Control theory provides systems engineering concepts to understand how dynamic feedback loops operate at multiple scales of time and abstractness for behavioral goals or targets (Carver and Scheier, 1982; Powers and Powers, 1973). Negative feedback reduces the discrepancy between the perceived situation and current goals in order to maintain goal pursuit, while positive feedback amplifies discrepancies to repel further from anti-goals. For instance, thermostats adjust temperature to close the gap between the current temperature and a reference temperature in a negative feedback loop. Blood clotting involves platelets releasing signals that attract more platelets to the injury site, compounding quickly to create distance from dangerously low levels of blood in a positive feedback loop.

Many aspects of everyday control behavior involve approaching a target goal or avoiding an anti-goal, in accord with negative and positive feedback loops (Carver and Scheier, 2001). For example, thinking outside the box involves approaching a creative idea and avoiding familiar and rigid mental sets. Indeed, cognitive computational neuroscience models using supervised learning instantiate positive and negative feedback loops to minimize or maximize multiple cost functions for cognitive control tasks (Miller et al., 1960; Botvinick et al., 2001; Rougier et al., 2005; Herd et al., 2014; Kool et al., 2017; Ritz et al., 2022). An effective control system is one that allows for reaching the widest range of routes to goal states efficiently, either in the world or our mind, despite great conflict and given diverse initial contexts and situations. These functional and algorithmic processes guide the investigation of the neural implementation of control.

Neural bases of cognitive control processes

“Nothing in excess”.

[— Delphic maxim (circa 6th century BCE)]

A century-old analogy for the neural bases of cognitive control considers how control regions of the brain act as a way station or switch that changes the flow of train traffic across a system of railroads (James, 1890). Some of the most influential current conceptualizations of control — the biased competition and guided activation frameworks — apply this analogy (Miller, 2000). The prefrontal cortex can be seen as a central station that implements cognitive control by redirecting trains carrying information about goals to manipulate the flow of command or stop signals at other stations, thereby biasing their activity to produce actions in line with goals (Desimone et al., 1995; Miller, 2000). Control signals coordinate traffic by adding trains, scheduling delays and slowdowns, and selectively admitting or banning only certain types of passengers using selective attention, inhibitory, and learning processes. All these activities help to maximize efficiency and minimize interference, redundancy, and conflict by avoiding traffic congestion as much as possible. There is correlative, causal, computational, and neurodevelopmental support for this framework (Park and Reuter-Lorenz, 2009; Somerville and Casey, 2010; Parvizi et al., 2013; Reuter-Lorenz and Park, 2014; Cavanagh and Frank, 2014; Luna et al., 2015; Marek et al., 2015; Cole, 2017; Widge et al., 2019).

Monitoring the conflict and congruency of goals and choices to switch tasks

Conflict arises from traffic across the brain, or the interference between simultaneously co-activating or spatially overlapping patterns of activity which represent competing or incongruent choices and goals (Monsell, 2003; Livnat and Pippenger, 2006; Musslick and Cohen, 2021; Frömer et al., 2019; Ritz and Shenhav, 2024; Held et al., 2024). Traffic from greater processing effort for error feedback or coactivation of conflicting response tendencies can make cognitive control aversive, cost time, feel difficult, and occupy mental resources (Kool et al., 2017; Fritz and Dreisbach, 2013). The dorsal anterior cingulate and medial prefrontal cortices detect conflict to signal error and to prioritize efforts, sending conflict signals that stimulate resolution among signals with more control (Botvinick et al., 2001; Narayanan et al., 2013; Shenhav et al., 2016). These efforts are coordinated by goal representations in prefrontal regions, acting as attentional templates to filter or bias downstream neural processing for multiple task rules, goals, opportunity costs, expected values, and levels of effort (Fuster and Alexander, 1971; Diamond and Goldman-Rakic, 1986; Goldman-Rakic, 1987; Funahashi et al., 1993; Asaad et al., 2000; Miller, 2000; Badre, 2008; Badre et al., 2009; Duncan, 2010; Shenhav et al., 2013; Mante et al., 2013; Stokes et al., 2013; Cole et al., 2013; Domenech and Koechlin, 2015; Freund et al., 2021; Badre et al., 2021). For example, dorsolateral prefrontal cortex is thought to bias attention and working memory to promote responses that are appropriate for goals while limiting responses that are inappropriate (MacDonald et al., 2000;

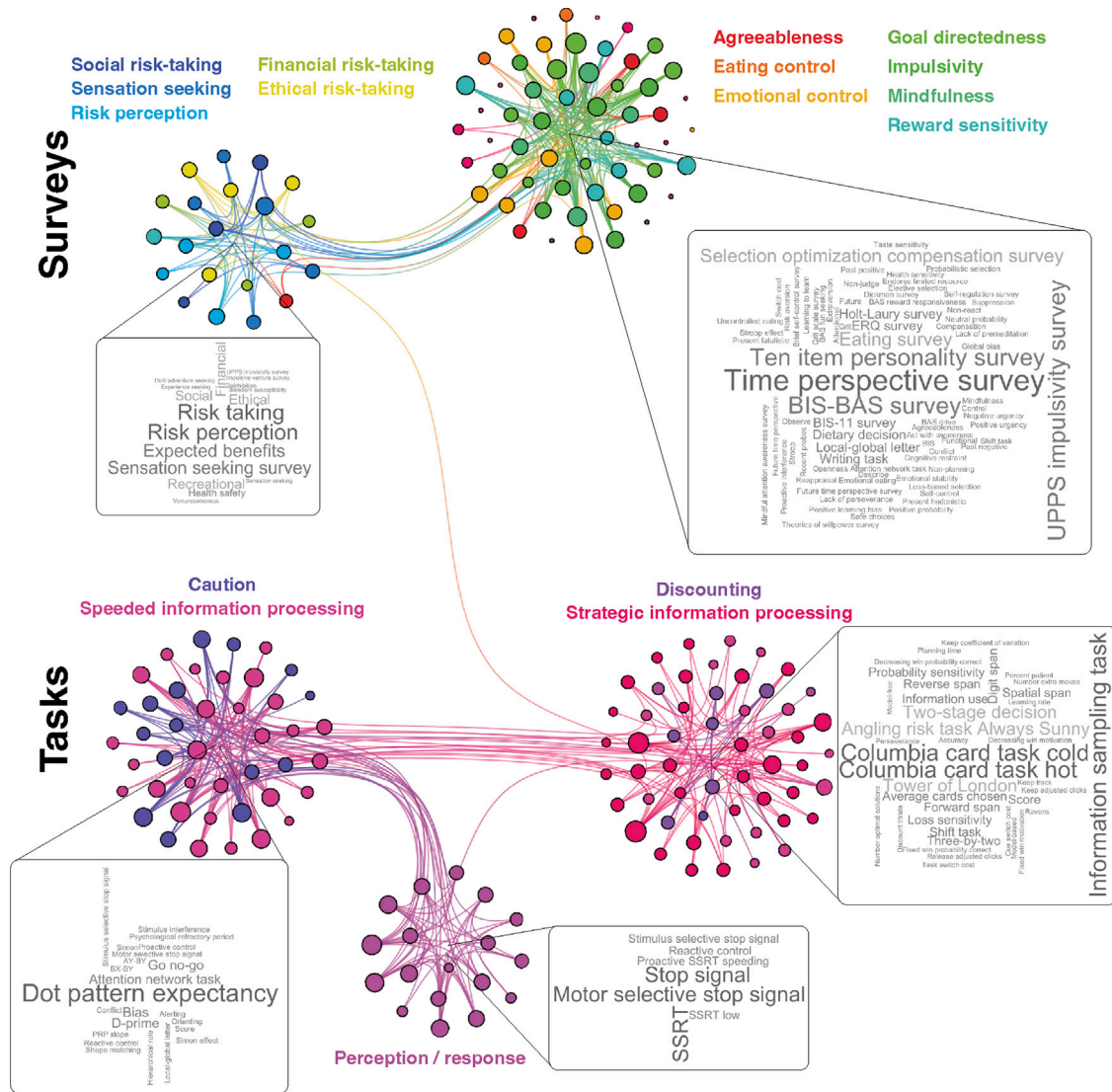


Fig. 2. Self-regulation measurements from tasks and surveys. Self-regulation often refers to processes that support goal pursuit broadly, and may benefit from but do not necessarily require certain forms of cognitive control (Fujita, 2011). Current survey and task measures, including cognitive control constructs, exhibit limited coherence (weak connections between task and survey modalities and within conceptual domains), suggesting the need to develop abstracted measures and models of cognitive control that bridge both tasks and surveys. We review evidence that network control theory relates to both task and survey variables, strengthening cohesion among constructs. A “cognitive ontology” is visualized using 129 task and 64 survey dependent variables reproduced from previously published data (Eisenberg et al., 2019). Nodes are defined as dependent variables which are colored and labeled by 5 task factors and 12 survey factors identified by the published exploratory factor analysis. Edges are defined as partial correlations between behavioral performance or self-report measures from 560 participants across all pairs of dependent variables. Edges are sparse due to moderate regularization ($\alpha = 0.15$) using Graphical Lasso and a partial correlation threshold of $r \geq 0.05$. Nodes are clustered based on a stochastic block model (Peixoto, 2014). Word clouds depict the node identities per cluster. See Appendix 4.2 and Eisenberg et al. (2019) for details.

Miller, 2000; Friedman and Robbins, 2022). Ventromedial prefrontal cortex is thought to predict outcomes relative to goals (Duncan et al., 1996; Alexander and Brown, 2011; Miller, 2000; Shenhav et al., 2013; Friedman and Miyake, 2017), regulating arousal and affect (Ochsner and Gross, 2005) as well as adapting to new information that is incongruent with previously learned information (Schiller et al., 2008; Moneta et al., 2023). Ventrolateral prefrontal cortex is associated with the selection of goal congruent response options among competing alternatives (Badre et al., 2005; Badre and Wagner, 2007). These specialized prefrontal regions communicate with a broader frontoparietal and cingulo-opercular network (Dosenbach et al., 2007; Jerde et al., 2012; Cole, 2017; Badre, 2020), including the anterior insula/operculum, dorsal anterior cingulate cortex, and thalamus (Cocchi et al., 2013; Sadaghiani and D’Esposito, 2015; Wu et al., 2019; Molnar-Szakacs

and Uddin, 2022). Such highly connected regions have many railroad connections, some which make U-turns back to the origin to allow signals to recur stably, that can help to flexibly enact control to modulate conflict, maintain stable control representations, and prioritize activity that is salient or relevant to goal representations (Rougier et al., 2005; Jerde et al., 2012; Botvinick and Cohen, 2014; Cole, 2017). As a form of reactive control, competing signals stimulate control signals to resolve conflict, increase resource efficiency, and improve performance by separating previously overlapping representations (Ritz and Shenhav, 2024; Braver, 2012; Jamadar et al., 2015). Conflict can also be preemptively avoided by proactively integrating multiple neural representations of the control task and goal (Badre et al., 2021; Kikumoto and Mayr, 2020; Kikumoto et al., 2024).

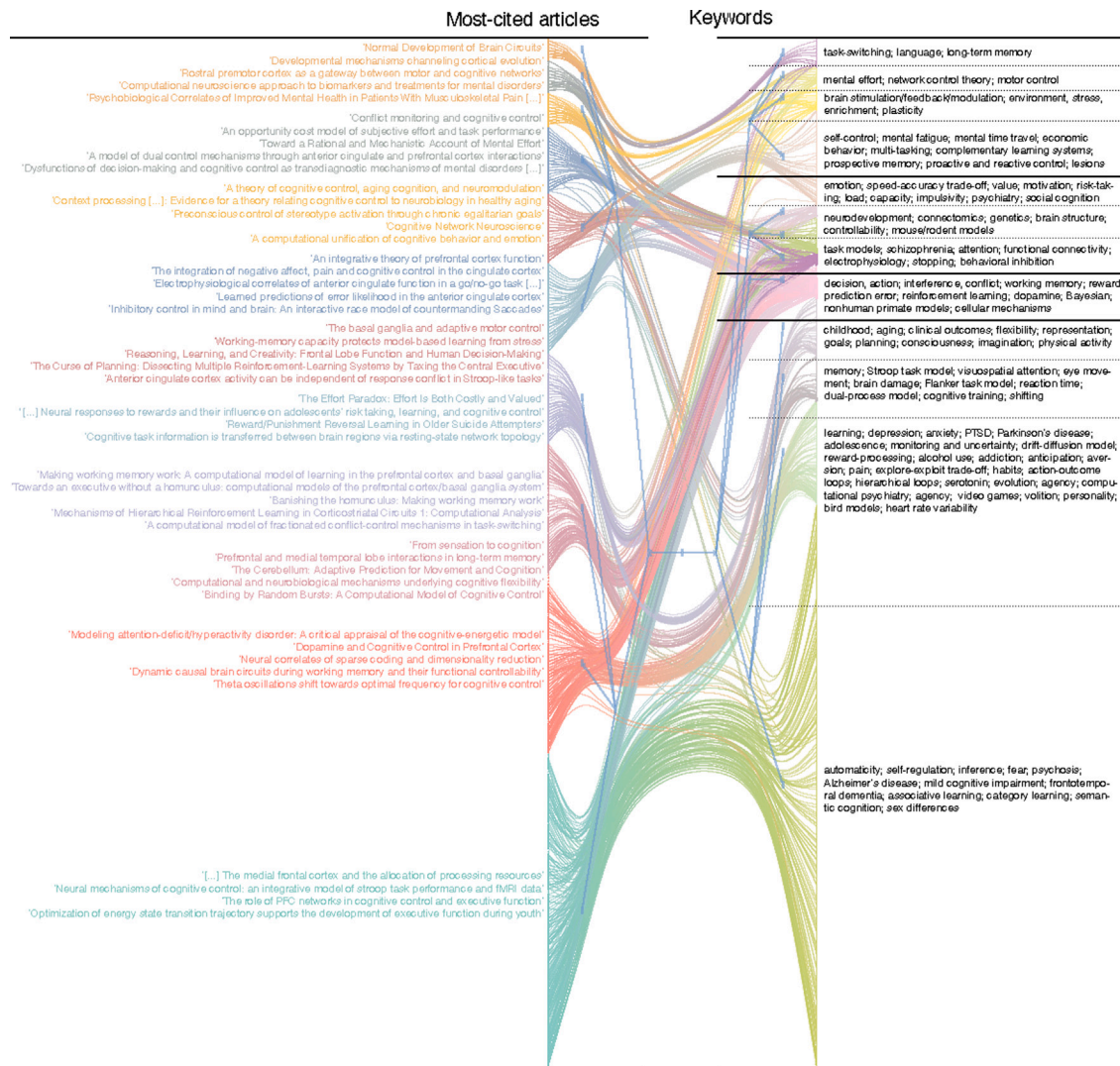


Fig. 3. A plurality of concepts from highly cited articles on cognitive control computations. The challenge is to develop a cohesive yet precise framework that can speak to a plurality of concepts at multiple levels of analysis. Visualization of a hierarchy of concepts from 308 highly cited papers that included the keywords “cognitive control” and “computational” from a Web of Science search. Topics determined by a hierarchical stochastic block model of an article-by-keyword co-occurrence network (Gerlach et al., 2018). For article nodes, we show five or fewer randomly selected articles in the community. For the keyword nodes, we show the most frequent words. Edges indicate co-occurrence. The blue tree network indicates hierarchical community structure, where the highest hierarchical level is demarcated by the solid and bold black lines, the middle level is demarcated by solid black lines, and the most granular level is demarcated by dotted black lines. Network control theory is a small branch of the concept hierarchy, yet is well-positioned as a theoretical and methodological framework to strengthen cohesion among the interconnected concepts. See Appendix 4.3 for details.

Stop signaling and behavioral inhibition

To alter control and conflict in accordance with goals, some inputs and outputs can be suppressed using the inhibitory signaling of corticostriatal loops and neuromodulatory pathways (de Kloet et al., 2021). Corticostriatal loops send stop signals from the striatum to cortical regions via thalamic anatomical projections, such as those maintaining information in working memory about goals and the task at hand (Frank et al., 2001; Wang et al., 2004; Frank, 2006; Aron and Pol-drack, 2006; Aron, 2007; Medalla and Barbas, 2009; Munakata et al., 2011; Aron et al., 2014). In concert with the inferior frontal gyrus (which includes ventrolateral prefrontal cortex), this fronto-striatal stop circuit inhibits automatized behavior to select actions in pursuit of a goal (Casey et al., 2002; Liston et al., 2006; Goghari and MacDonald, 2009; Aron et al., 2014). As such, striatal involvement provides a bottom-up control signal that complicates predominantly top-down views of cognitive control.

Value and salience shapes goal-oriented perception, choice, and learning

Valuation and salience processes also help alter control and conflict activity in accordance with goal representations, calculating which actions to select or suppress in relation to a goal using parallel corticostriatal loops and neuromodulatory signaling (Daw et al., 2005; Seeley et al., 2007; Cools, 2008; Cools and D'Esposito, 2011; Botvinick and Cohen, 2014; Cools, 2015; Rmus et al., 2021; McDougale et al., 2022). Salience processes function to segregate the most behaviorally or homeostatically relevant stimuli among conflicting internal and external stimuli to guide behavior, where relevance is signaled by motivation, valuation, and affective systems. The ventromedial prefrontal cortex and striatum interact with the dorsal anterior cingulate cortex to support the valuation of the potential courses of action that integrate affective and salience inputs through connections with the anterior insula (Seeley et al., 2007; Menon and Uddin, 2010; Shenhav et al., 2013; Ochsner and Gross, 2014; Wu et al., 2019; Molnar-Szakacs and Uddin, 2022). At the neuronal level, incoming and outgoing connections are

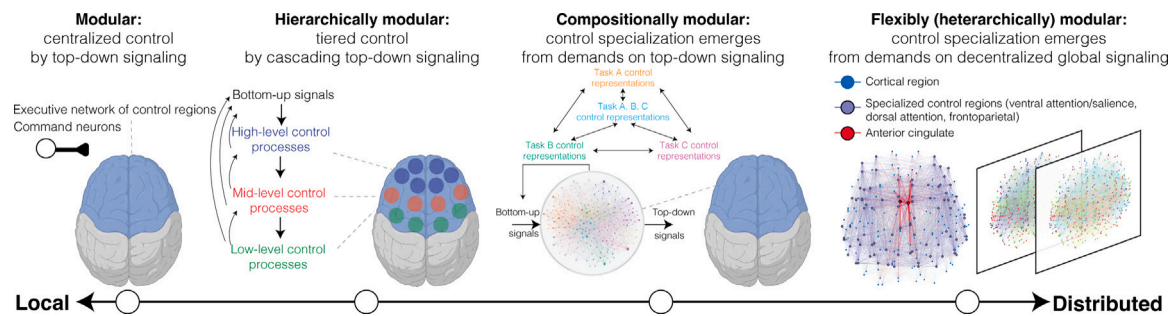


Fig. 4. Local and distributed control signaling. Hypothesized control processes place differing importance on centralized versus decentralized signaling (Eisenreich et al., 2017). *Modular control* is largely encapsulated and centralized within a few regions with distinct biological composition to output top-down signals. *Hierarchically modular control* partitions processes along a stratified ladder, maintaining separation of function as top-down signals cascade down the rungs and feed back signals to monitor progress. *Compositionally modular control* emerges from interactively integrable representations learned to meet the demands of control behavior to output top-down and feedback signals. *Flexibly modular control* emerges from representations meeting the demands of control behavior engaged by global top-down, bottom-up, lateral, and recurrent signaling. In contrast to a hierarchy, a heterarchy involves varied modules that consolidate and dissipate over time according to demands on global signaling. Control signals evolve simultaneously and in parallel across neural systems. Which signals lead or follow is relative to the perspective of the scientist (analogous to opening a chain loop to define which link leads and which follows; the break sets which element appears first). These hypotheses can be complementary and need not be mutually exclusive—a heterarchy can involve a temporary hierarchy containing compositional representations in hierarchically nested regions with specialized local biological compositions. Brain image is from BioRender.

prone to change such that useful transit lines are more heavily traveled and reinforced by positive feedback or are quieted and closed by negative feedback from other stations, a learning-dependent plasticity that helps save, monitor, and improve progress (Tolman, 1948; Cohen et al., 1990; O'Reilly and Frank, 2006; Herd et al., 2014; O'Reilly et al., 2016).

Brain-wide top-down and bottom-up signaling and neural signatures of cognitive control

Theories place differing importance on top-down signaling relative to other forms of signaling (Miller, 2000; Eisenreich et al., 2017) (Fig. 4). Signals of goals, conflict, and stopping are types of top-down signals that filter, amplify, trigger, and redirect certain bottom-up inputs via communication and control (Srivastava et al., 2020). For instance, bottom-up perceptual signals are biased to select or suppress the parts that are most or least relevant to current goals (Desimone et al., 1995; Noudoost et al., 2010; Muller et al., 2018). The collective activity of top-down signals may be enacted by alpha, beta, and theta oscillations from deeper cortical layers, traveling from anterior to posterior regions of the brain (Aron et al., 2016; Cavanagh and Frank, 2014). These top-down signals may modulate bottom-up gamma bursts from superficial cortical layers to bias perceptual signals as they propagate to task functional regions (Lundqvist et al., 2023; Miller et al., 2024). Striatal, insular, and thalamic loops further suggest that motivation, social cognition, reward, and emotions are core signals that dynamically interact with top-down signals, complicating notions of a predominantly top-down hierarchy of control (Deci and Ryan, 2000; Pessoa, 2009, 2023; Stalnaker, 2024; Leung et al., 2024; Hofmann, 2024). Recent approaches focusing on neural signatures remain more agnostic to such theories and models of neural systems, and instead classify and decode the patterns of activity across the brain that indicates when a person is actively engaging in cognitive control processes (Schneck et al., 2023; Rieck et al., 2024; Herzog et al., 2025).

Summary

Control emerges from top-down selective attention or inhibitory gating processes that bias the inflow and outflow of bottom-up signals to filter, amplify, trigger, or redirect parts of the signal related to goal representations. Continuously monitoring the situation, other regions detect conflict between top-down and bottom-up signals to stimulate more control adjustments according to value, cost, and perceived progress.

Limitations and tensions of current psychological and neuroscientific approaches

"[T]here occurs a kind of progression in industrial discipline moving from paternalistic controls to assembly line, machine paced routines and, finally, to bureaucratically imposed discipline. What is involved is a shift from heteronomous paternalist controls to autonomous, internalized discipline, and identification with corporate goals and values".

[— O'Neill, 1986]

Current constructs have several limitations and tensions at the neural and behavioral levels, as well as at the cultural and normative levels.

Neural and behavioral tensions

First, it remains unclear exactly how the implicated neural activity represents goals, rules, conflict, costs, benefits, options, actions, and feedback, let alone how different perceptual, affective, motivational, motor, and control representations are integrated with them. In computational models that have incorporated neurophysiological processes and aim to model a cognitive control region's function (e.g., prefrontal cortex), the propagation and transformation of activity allows it to generate cognitive control behavior, dependent on that activity originating from a source that already encodes these kinds of relevant information (Cohen et al., 1990; Cooper and Shallice, 2000; Botvinick et al., 2001; Botvinick and Plaut, 2004; Cooper and Shallice, 2006; Herd et al., 2014; Bustamante et al., 2021; Prystawski et al., 2022). Ongoing work aims to explain how cognitive control representations are neurally encoded (Frank, 2006; Miller et al., 2003; Hazy et al., 2006; Freund et al., 2021; Miller et al., 2024; Kikumoto et al., 2024; Ritz and Shenhav, 2024; Badre et al., 2021; Kikumoto and Mayr, 2020; van Ede et al., 2020; Yang et al., 2019).

Second, what counts as "good" cognitive control is ambiguous at the neural and behavioral levels because it depends on context. Different instances of control behavior can be shown to depend on different neural systems. For example, a cognitive control task that focuses on personally or socially relevant goals elicits default-mode activity compared to tasks that focus on more contrived goals (Spreng et al., 2014; Shenhav et al., 2013). Moreover, different valuation processes can change what counts as success vs. failure for the exact same control behavior (McGuire and Kable, 2013; Kidd et al., 2013; Sutlief et al., 2025). For example, whether a measure like reaction time, variability, high cost, learning rate, momentary hedonism, or sensation seeking

indicates good or bad control is context dependent (McGuire and Kable, 2013; Kidd et al., 2013; Eisenberg et al., 2019; Thomson and Oppenheimer, 2022). This ambiguity arises because many models are underconstrained (Mischel and Ebbsen, 1970), allowing many (sometimes contradictory) ways to explain the same behavior. Fortunately models can incorporate a broader scope of relevant conceptual and neuroscientific variables (McGuire and Kable, 2013; Kidd et al., 2013; Lieder et al., 2018; Heffner et al., 2021; Bustamante et al., 2021; Schurr et al., 2024; Silvestrini et al., 2023; Shenhav, 2024).

Cultural and normative tensions

Third, a limited set of behavioral instances of control tend to be studied, and those instances seems to cater to societal norms and beliefs about control that are desirable or virtuous. Blending the biology and culture of control blurs the line between self-discipline by internally generated goals and discipline imposed by societal norms (O'Neill, 1986; Ryan et al., 1995; Deci and Ryan, 2013). When construed as encompassing all goal-directed behavior in general, cognitive control can be used to pursue any goal. Yet out of all the countless possible goals that could be pursued, a relatively small set of norms drive outsized attention to goals that seem selected for fitting a certain set of sociocultural expectations about asceticism, mortification (subduing one's "earthly nature" and sinful impulses through self-denial), and transgression that can be traced to philosophical and religious literature over two millennia. Striving for temperance, personal responsibility, and meritorious achievement certainly may lead to healthier, happier, and more productive lives and communities (Robson et al., 2020; Moffitt et al., 2011; Duckworth and Seligman, 2005). It is perhaps unsurprising that endorsement of such norms is related to normative metrics of success that are partly defined by self-surveillance according to those norms (Eisenberg et al., 2019). But are those goals not more properly value judgments, spiritual exhortations, or moral presuppositions instead of a fundamental neurobiological and cognitive function, even though much could be said in their favor (Duckworth and Seligman, 2005; Blair and Razza, 2007; Moffitt et al., 2011; Mischel et al., 2011; Robson et al., 2020)? One wonders how experimental tasks, extant control representations, and outcome metrics of success in life would change if creativity, compassion, cooperation, or altruism were elevated. Just as one could expand the scope of goals and flourishing, conversely, one can readily construe goals wherein strong control leads to guilt, shame, isolation, oppression, deceit, and violence. Or one could construe goals that appear frivolous, fanciful, or impossible (Chu et al., 2024). Normative assumptions reflect the current zeitgeist, but such assumptions not only threaten generalizability across studies and cultures (Munakata and Michaelson, 2021), but generalizability across time and to other species. There is an ambivalence to cognitive control, more like perception or movement than a virtuous vehicle to prosperity.

Fourth, cognitive control is not a universal recipe to take action and reap rewards. General applicability to all goals tempts a perennially enticing belief in an inner fuel — like willpower — that can get us to wherever we set our minds to: "where there is a will, there is a way" (Inzlicht and Berkman, 2015). In contrast, there is inconsistent evidence for broad applicability of control leading to desired outcomes (Blair and Razza, 2007; Moffitt et al., 2011; Duckworth and Kern, 2011; Burman et al., 2015; Randles et al., 2017; Eisenberg et al., 2019; Enkavi et al., 2019), evidence for more specific and local transfer across goals based on the type of control strategy and task (Rougier et al., 2005; Collins and Frank, 2013; Duckworth et al., 2016, 2018; Bustamante et al., 2021), and a lack of relationship between control components and putative domain general constructs of intelligence (Friedman et al., 2006). Willpower is thought to enable mastery over oneself and, with some luck, imposition of one's will on the environment and others. This is power misidentified as willpower. The temptation to confuse power for willpower may be explained by how it empowers people to take responsibility for their fate, a link that justifies why certain people deserve power and others do not, to appear

greater than their fortune. One problem that this confusion creates for the science of control is constraining the space of hypotheses to indulge what some may already want to believe—that we can achieve whatever we set our minds to, that we can bend the world to our will, and that clear ambition and focused effort fan fortune towards these ends. These are beliefs about power. When applied to cognitive control, those beliefs support the idea that individual differences in control and their purported outcomes are not only justified but biological. Such beliefs in willpower are outmoded in cognitive control (Inzlicht and Friesse, 2019) and supplanted by dynamic feedback loops of perception, valuation, and action. We do not have worse cognitive control because we lack the strength or capability of will. Rather, worse cognitive control occurs when there is a large discrepancy between what we perceive a situation demands of us and what we have learned to subjectively evaluate as being worth doing, too costly to change, and as opportunities too regrettable to lose given limited time and attention. Nevertheless, a remarkable causal and explanatory power is still often assumed of cognitive control as a solution for the many outcomes that life seems to demand of us, whether or not they arise from our own values. Confidence in this assumption appears disproportionate relative to the construct's modest internal coherence, its modest predictiveness of outcomes with many possible unconsidered causes, and the negative outcomes of its overuse (DeCaro et al., 2011; Smithers et al., 2018; Eisenberg et al., 2019; Munakata and Michaelson, 2021; Bustamante et al., 2021).

Finally, many current conceptualizations of control have an issue known as the "homunculus" problem, because they postulate internal representations of goals and processes that themselves manage control in the same way a person might. While a homunculus is no longer as explicit as it once was — embodied, for example by Plato's notion of a charioteer of reason or a more recent notion of a central executive CEO who organizes information in their prefrontal office to pursue goals (Plato, 1952; Baddeley, 2002) — there is still a passing resemblance to human-like controllers in many models, such as an economist evaluating information with rational cost-benefit analysis to maximize the expected utility of exerting control. Although these metaphorical sources of control are not explicitly posited by any modern theory (Hazy et al., 2006; Aron et al., 2016; Fuster, 1990; Ochsner and Gross, 2014; Carver and Scheier, 2001), they are often implied by or necessary to models' formulations, from will to utils. This has been the case since the classic model of dynamic test-operate-test-exit feedback loops, which resembles control by business managers. In a dynamic process with top-down authority and hierarchical communication channels, executive goals set worker objectives, progress is monitored and evaluated, and rewards or punishments are delivered (Miller et al., 1960; Drucker, 1954; Simon, 2013). Quantifiable goals and task delegation to specialists maximize the efficient distribution of labor and minimize conflicts that prevent resources from being optimally allocated: two strategies with origins in business management (Taylor, 1919; Doran, 1981; Simon, 2013). These are useful and ubiquitous cognitive and cultural tools deserving of application and study, but treating life as if it is a business risks mistaking management metaphors for the nature of self-management. Using metaphors is not necessarily problematic. Metaphors help generate ideas, and they are not necessarily even wrong. After all, humans behave in a world governed by values, traditions, and economics. The issue is when parts of metaphors at the behavioral and psychological level also map out the neural and physical levels. The problem is not that scientists seriously endorse homunculi, but that large knowledge gaps left unexplained about the neural representations of control concepts can implicitly rely on the intuition of homunculi to hammer out and haunt those very voids.

Summary

We often impose cultural ideas of what control should do onto our models of how control works. The CEO is one such idea, traditions that emphasize rational and virtuous control is another example, and the simplistic idea that people succeed in life because of willpower, where willpower is the currency of control, is another example. The field has already reckoned with many of these nuances, but they have a stubborn influence. It is difficult to cleave ideas that have endured for over two millennia. A neurobiological process model of cognitive control can offer mathematical explanations that help address or circumvent some of these challenges (Eisenreich et al., 2017; Pessoa, 2023; Noble et al., 2023; Ross, 2025).

The network control theory construct of control

“It is not necessary, however, to organize one’s Plans in terms of frozen and brittle terminal states. Unlike good problems in science or mathematics, successful living is not a “well-defined problem”, and attempts to convert it into a well-defined problem by selecting explicit goals and subgoals can be an empty deception. [It] is better to plan toward a kind of continual “becoming” than toward a final goal”.

[— Miller et al., 1960]

Originally formalized in the field of systems engineering, control theory has been applied to regulate the behavior of systems in technology, communication, transportation, and robotics (Kirk, 2004; Liu and Barabási, 2016; Brunton and Kutz, 2022). In neuroscience and psychology, different forms of control theory have helped to understand perception, movement, reward-guided decision making, self-regulation, and psychopathology (Marken and Mansell, 2013; Todorov and Jordan, 2002; Shenhav et al., 2013; Shadmehr et al., 2016; Shenoy and Kao, 2021; Ritz et al., 2022; Carver and Scheier, 2001; DeYoung and Krueger, 2018). Here we describe how network control theory can be applied to understand the neuroscience of cognitive control, at a high level with no assumptions of prior mathematical background.

Basics ingredients of network control theory

As noted above, current models of control in psychology and neuroscience (e.g. the biased competition and guided activation models) describe control regions as implementing top-down signals that have a biasing effect on other regions, guiding their activity as if providing instructions for how to move trains in a system of railroads (James, 1890; Miller, 2000; Cole, 2017). By contrast, network control theory formalizes these ideas into a cohesive framework by explicitly specifying the kind, amount, location, and timing of activity across the brain expected to enact such control. On this view, an effective control system allows for efficiently reaching the widest range of routes to goal states, given diverse initial contexts and situations. The extant literature on network control theory in neuroscience primarily operates at the level of how control is implemented to efficiently reach the widest range of routes to brain states.

To illustrate how network control theory works, elements of the railroad analogy (James, 1890; Miller, 2000) remain useful, including the railroads, trains, routes, ongoing traffic, target traffic pattern, and train conductor. In place of railroad tracks, neural signals have the hard constraint of continuously propagating across the anatomical white matter pathways between regions, which can be measured by diffusion imaging (Fig. 5A). Methods to estimate effective connectivity from activity have also been used to model this constraint (Scheid et al., 2021; Rouse et al., 2023). These “tracks” converge at different “stations” or brain regions.

In place of informational “trains”, the *spontaneous dynamics* of each region is determined by propagating threads of activity—signals sent by one region to neighboring regions and still others across their anatomical connections (Fig. 5B). The magnitude of activity is amplified or constrained according to the strength and volume of the connections

it travels across. When multiple threads of activity intersect at the same region, their activity is summed, further propagated to connected neighbors, and decays over time.

Due to the hierarchical hub-and-spoke connectivity of the brain Bassett et al. (2010), what started as hundreds of threads of activity splits off into hundreds of thousands of simultaneous threads as each thread splits off at more and more regional intersections. Due to the small-world modularity of brain structure (Bassett and Bullmore, 2006), after crossing just four or five intersections, threads provide multi-step functional pathways between all regions, although longer functional pathways are far less reliable and more costly to traverse than shorter pathways (Zhou et al., 2022b; Seguin et al., 2023). The mathematics used to calculate the predicted future behavior of these dynamics precisely formalizes how much, where, and when neural signals have “downstream influence”(Fig. 5 C).

The *control energy* is the amount of additional activity that is needed to account for the difference between the future activity predicted in spontaneous dynamics and the amount of future activity that serves as a *control target*. When network control theory is applied to behavioral control tasks, control targets are patterns of activity elicited by a goal or cognitive control task, analogous to prior cognitive and computational neuroscience approaches. Defining control targets as future patterns of task-evoked activity can map network control to previously studied activity implicated in the component processes of a cognitive control task (in a standard fMRI analysis, this is a general linear model’s beta coefficient). There are also other sensible choices for defining control targets, including measurement units from machine learning classification or decoding methods that index neural signatures of cognitive control, as well as the evolution of neural activity measured with electrophysiology, spike recording, and calcium imaging (Shenoy and Kao, 2021). When control targets are defined as measured activity patterns, network control theory is a theoretical model of how the brain regulates activity that was evoked by and continuously evolved with what was viable for a task and situation, emerging from the perception, valuation, and action loops operating from moment to moment. Control targets self-organize according to task and context. To drive the target activities that the brain was measured to have enacted, network control theory details how brain wiring and dynamics efficiently regulate activity towards any hypothetically reachable target. This allows for flexible definition of control targets. Modelers can also use network control theory as a methodological tool to consider counterfactual control targets, asking “what if” the brain self-organized differently? They can build in but are not bounded by what is considered as a “correct” behavior in a well-defined task, providing a useful theoretical foundation for yet unconsidered control targets.

The amount of energy needed to attain a target pattern of activity can be likened to a calculation of the energy needed to redirect a sailboat towards a target direction by reorienting its sail against the naturally changing currents of wind and water (Fig. 5C-D). The “energy” in control energy refers to the cost of additional activity ramping up quadratically (input activity²). This quadratic form of energy is both a mathematical convenience, allowing solutions to closed-form equations and numerical simulation, and is theoretically motivated. The form prohibits exceptionally large deviations which are not empirically observed in biology due to biophysical constraints (Sterling and Laughlin, 2015). Stable, linear feedback systems operate in this manner, which indicates that the linear dynamics are provably stable and stay within biologically viable bounds.. Despite the different name, energy has the same behavior as the propagating threads of activity described above. Different regions have different available solutions to the control problem of how much, where, and when energy input would usefully add to spontaneous activity to control the evolution of activity to control targets with the allocation of as little control energy as possible. Control energy — just as neural activity and its underlying neurophysiology — does not simply deplete, as posited by resource models of control in psychology whose empirical support has eroded (Inzlicht and Friese,

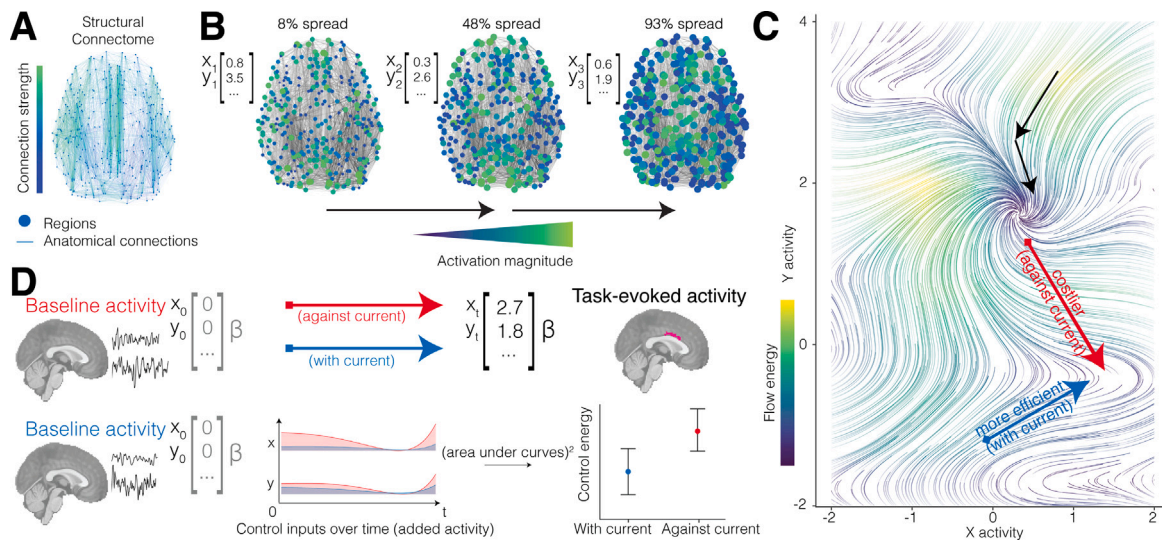


Fig. 5. Guided activation according to network control theory models of spontaneous and controlled activity flow. (A) The anatomical connectivity of the brain, as defined by a structural connectome. (B) Neural activity spreads across anatomical connections over time (Avena-Koenigsberger et al., 2018; Zhou et al., 2022b; Seguin et al., 2023). For illustration, consider just two regions (though all are modeled). From an initial state, the change in activity for region X and region Y over two transitions: (x_1, y_1) to (x_2, y_2) and (x_2, y_2) to (x_3, y_3) . The activity values can be predicted linearly, meaning that regional activity is calculated by taking the source activity multiplied by the connection strength and adding it to the target's activity. Linear dynamical systems theory allows us to solve this calculation across all regions and connections simultaneously and understand how global activity patterns emerge from local regional connectivity profiles per time step. (C) A conceptual schematic showing how region X and region Y 's activity flows over time. The two transitions from Panel B are drawn with black arrows. Simulating the predicted activity from many different initial points can provide a comprehensive understanding of the dynamical flow of activity, visualized as streamlines. Streamlines drive activity flow away from zones of higher energy (yellow) to zones of lower energy (blue). The controlled transition between some states (red arrow) must overcome a stronger current of natural dynamics than that between other states (blue arrow). (D) Consider a control problem that starts at two different baselines for the same person. The problem of control is to solve for the minimal time-varying input to add to the natural dynamics to reach the pattern of activity serving as the control target. Here, consider the control target as dorsal anterior cingulate cortex activity evoked during a control behavior that is thought to signal the levels of cognitive conflict and goal congruency to switch tasks (Zhou et al., 2025; Holroyd, 2025). The control energy is the square of the integrated input added over time such that the energetic cost rises steeply per unit of input. Greater energy is needed for the red trajectory because it must overcome stronger currents of natural activity flow than the blue trajectory. Network control theory provides closed form solutions and tractable numerical simulation tools to find optimal solutions for this problem given any selection of initial states and control targets, and does so simultaneously for any set of regions and connections per time point.

Source: Figures reproduced and adapted from Zhou et al. (2022b, 2023a).

2019). Instead, control energy characterizes continuous readjustments to brain activity by their neural cost, reactively sensitive to inputs such as changing goals or proactively anticipating the demands of the control task in a dynamical prediction feedback loop ("allostasis") (Ashby, 1952; Braver, 2012; Sterling, 2012; Zhou et al., 2023b; Theriault et al., 2025; Mehrhof et al., 2025; Zhang et al., 2025).

In place of train traffic causing congestion, interference, and conflict which signal the need for cognitive control, spontaneous activity demands more control energy when it naturally deviates from the control target. As such, cognitive control is not only the consequence of a terminal control target — the activation or deactivation of key brain regions passing some threshold — but is a function of the moment-to-moment processes that guide evolution towards that outcome and continue after that outcome. Network control provides a mathematical model for these continuously evolving functions.

In place of supervision by a metaphorical train conductor or switch operator that follows certain rules and instructions, in network control theory, regions are better network controllers when they mathematically have more possible, or less energy-intensive, routes to control targets. Given the fact that activity continuously flows between regions at all times, good control regions are points in the network where control energy combines with spontaneous activity to effectively distribute the changes in activity levels towards control targets—a dynamic feedback loop constrained by the physics of the brain.

Convergence and expansion of predicted network control points with prior regions of interest

Intriguingly, while all regions could contribute to this continuous and distributed control process, the theory converges on a similar set

of regions as prior investigations due to their advantaged placement for adjusting the flow of activity, including the dorsolateral and ventrolateral prefrontal cortex, superior parietal cortex, dorsal anterior cingulate cortex, thalamus, insula, and frontoparietal network broadly (Cui et al., 2020; Zhou et al., 2023a, 2025; Miller, 2000; Gu et al., 2015; Betzel et al., 2016; Cole, 2017) (Fig. 6). Importantly, the theory also naturally produces graded predictions of other key network control points likely to be involved in the dynamic feedback loop of perception, valuation, and action (Betzel et al., 2016), across brain regions and traditionally segregated psychological functions that have been unconsidered, marginalized, or indirectly linked due to variations of task design. These control points include the orbitofrontal cortex (Eisenreich et al., 2017), caudate and putamen (Lopez et al., 2014; Chiu et al., 2017), hippocampus (Lengyel and Dayan, 2007; Chung et al., 2021; Agrawal et al., 2022; Park et al., 2025), premotor regions (Fine and Hayden, 2022), default-mode regions like the precuneus or posterior cingulate cortex (Spreng et al., 2014), visual regions (Powers and Powers, 1973; Fuster, 1990), allostatic-interoceptive regions (Zhang et al., 2025), and amygdala (Pessoa, 2009; Salzman and Fusi, 2010; Inzlicht et al., 2015; Pessoa, 2017).

Intuitions about cognitive control from the mathematics of network control

Having provided a conceptual overview of network control theory, an important next step is formalizing these core ideas with mathematical concepts. Consider the problem of needing to direct activity in a network to control targets, which are the activity patterns associated with a goal or conflict representation. Each target pattern can be represented as a list of activation values $[t_1, t_2, \dots, t_n]$ for n

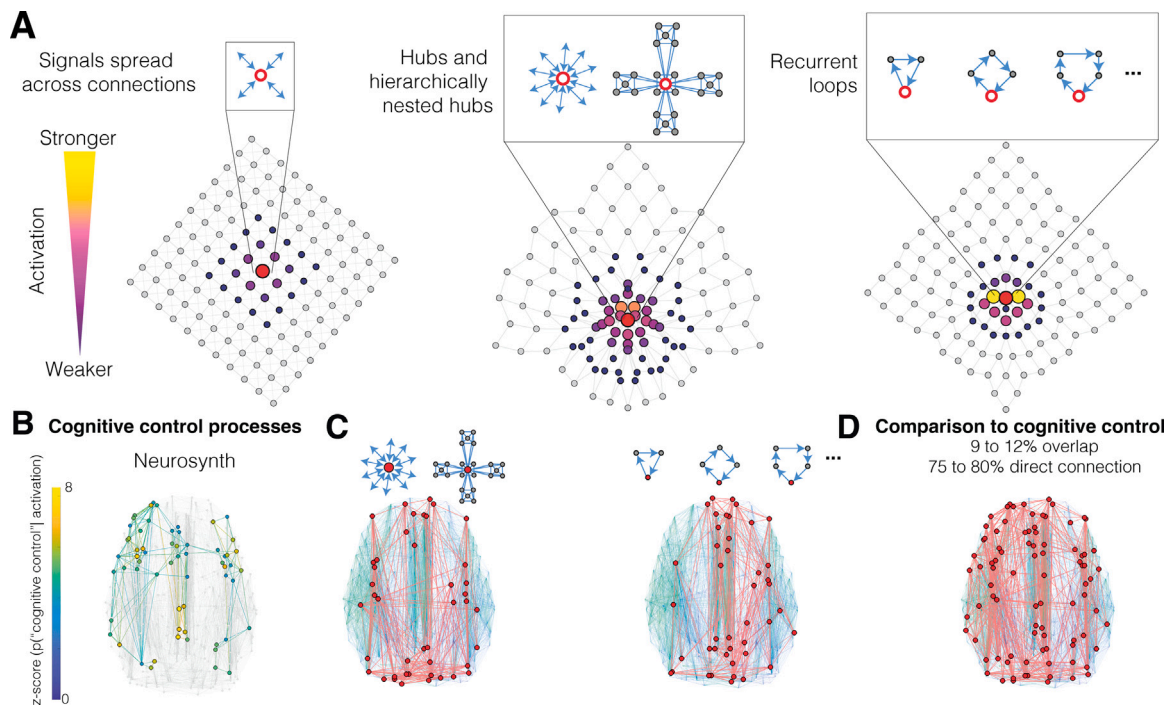


Fig. 6. Nested and recurrent organization of networks shape activity flow. (A) Linear dynamics makes explicit predictions for how connections influence global signal flow for a given region (Avena-Koenigsberger et al., 2018; Zhou et al., 2022b; Seguin et al., 2023). For illustration, let us consider different impulse responses, or how different connectivity profiles for a single source region (red node) influence the spread of activation when the red node receives input. Continuous-time dynamics were simulated using the *nctpy* toolbox (Parkes et al., 2024). *Left*: When the source is embedded in a grid organization, activity spreads evenly. *Middle*: In contrast, if the source region is a hub — having many more connections than its neighbors — then the activity can spread farther, pulling distant nodes inward to be more reachable by using the hub's many connections. *Right*: If a source region has many more recurrent connections looping back to itself, then activity spreads more than on the grid and in a more concentrated pattern around the source than the hub. Recirculated activity out-competes global spread. These explicit dynamical predictions show how the global activity can be influenced by the differing connectivity profiles of a single source. Network control theory allows us to model multiple simultaneous sources with time-varying input. (B) Do regions involved in the cognitive control loops of perception, valuation, and action exhibit recurrent connectivity, suggesting control loops operate at multiple levels? A cognitive control network is visualized, where nodes are highlighted from a Neurosynth meta-analysis of the term “cognitive control” with voxels FDR-corrected at $q < 0.01$ and regions at $z > 3.3$ (Yarkoni et al., 2011). Overlaid on the structural connectome, where edges are highlighted if a direct anatomical connection exists between regions of interest. Gray nodes and edges do not pass statistical thresholds. (C) The brain has a mixture of connectivity profiles and multiple regions are potential sources of simultaneous activity flow. Highly connected and recurrent hubs most efficiently distribute control inputs to engage control targets (Betzel et al., 2016; C. Gratton et al., 2018; Patankar et al., 2020). *Left*: Hubs with stronger connections than expected by chance comprise a “rich-club” of about 12% of all regions. *Middle*: The strongest anatomically recurrent hubs comprise about 12% of all regions. (D) There is an 89% overlap or direct connection between hubs and the cognitive control nodes, which in combination comprise 27% of brain regions with highly efficient signaling to the other 73% of brain regions. Subcortical regions are not included for illustration but see Betzel et al. (2016). See Appendix 4.5 for details.

brain regions. In the context of the railroad analogy, this process is like figuring out how many ways you can arrange ready-made pieces of railroad tracks of fixed length and curvature to reach different target destinations (Fig. 7). This control problem has multiple solutions constrained by the physics of the brain. Each solution is a different way of factoring one of the target activities t as a summed combination of several repeatable factors x , y , and z , which represent the strength of anatomical connections through which activity flows. Some target destinations are farther than $x + y + z$, necessitating some repeats of each a , b , and c times, respectively. Taken together, this structure makes the control problem $t = ax + by + cz$. For example, there are 14 ways of combining the tracks $x = 0.5$, $y = 0.4$, and $z = 0.3$ into the target $t = 3.6$ (Fig. 7A). The number of possible solutions to this equation characterizes the probability of control. The quantity $(a+b+c)^2$ characterizes how using a large number of tracks steeply ramps up the energy cost with the squared exponent. This form is a theoretical consequence of the simplifying approximation of linear dynamics such that activity evolves in a manner that is reducible to the additive and multiplicative contributions of particular regions and the strength of their connections. Following the previous example, the most efficient solution to factor $t = 3.6$ is to combine x four times with y four times for an energetic cost of $(a+b+c)^2 = (4+4+0)^2 = 64$. The most expensive

solution combines x once, y once, and z nine times for an energetic cost of $(a + b + c)^2 = (1 + 1 + 9)^2 = 121$. Easier and efficient network control has less energetic cost.

Easy and efficient control is less effortful in the sense of marshaling fewer regions and connections to propagate threads of control energy (activity). For easy and efficient control, it is useful to have x , y , and z be large because only a few tracks would be needed to make substantial progress towards the target sum. It is also efficient to have a chain of connections that form strong recurrent pathways because an echo of a previous factor can be recycled in a partially diminished form to advance towards the sum without needing to further increase a , b , or c . The advancement persists, saving progress.

Easy and efficient control further benefits from having additional tracks beyond x , y , and z , such as w . For example, adding just one more train track w into the mix, so that we have four rather than three pieces available, increases the number of solutions from 14 (Fig. 7A) to 89 (Fig. 7B). Having additional tracks is characteristic of hierarchically connected hubs, which are highly connected regions that act as nexuses of activity due to widespread connectivity that forms an information backbone for neural communication (Mesulam, 1998; Van Den Heuvel et al., 2012; Gratton et al., 2016; C. Gratton et al., 2018; Badre, 2020; Zhou et al., 2022b,a). Having more tracks allows for a substantially

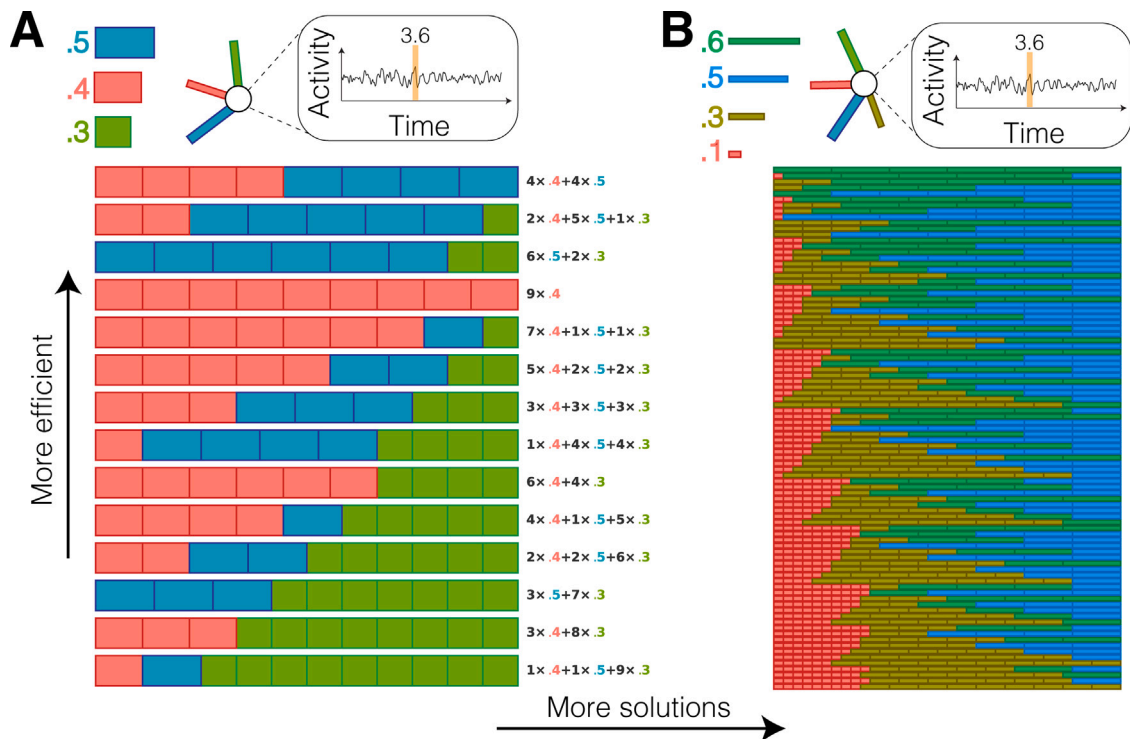


Fig. 7. Making train tracks: developing mathematical intuitions about easier and more efficient control. (A) Akin to finding all the combinations of railroad tracks in a toy train set that can be used to reach a target destination, the idea underlying the mathematical formalization of control can be illustrated as finding all of the ways to make a target pattern (summed activity magnitude of 3.6) with a node (akin to a station) that has three connections of strengths 0.5, 0.4, and 0.3 (where each connection is akin to the specific shape of the railroad track). Each row is 3.6 units of activity wide and specifies one possible solution given the target magnitude and factors. More efficient solutions for reaching the target pattern use fewer connections (akin to the pieces of the track). **(B)** Adding just one more connection vastly increases the repertoire of possible control solutions.

greater repertoire of control solutions and a larger number of efficient possibilities (Betzel et al., 2016; Cole, 2017), including stabilizing a current state. Such stability emerges not only from efficiency but from being tethered to more neighbors, aggregating activity changes in many directions and muting rapid fluctuations for lower frequency oscillations of activity that may support information integration for external sensorimotor events, as well as internal decision making, motivation and memory processes (Canolty and Knight, 2010).

In contrast, for difficult and fine-grained control, it is useful to have a diverse range of connection strengths (Kim et al., 2018). When x , y , and z are all relatively large, it can create big changes to the sum or a persistent momentum that easily overshoots or strays from the control target pattern of activity t . For a greater number of solutions, it is useful to have some small tracks as well, but this comes at a greater cost to $(a + b + c)^2$ from using small tracks many times. Such small additions are more transient, lacking the hefty structural support of hubs to recycle activity. But what is granted is the ability to flexibly turn to new directions with precision, like making a sharp rather than wide turn when driving a compact car versus a truck. For example, a long track travels farther along before a new change in direction is possible, whereas a short track ends quickly allowing for more frequent changes to target destinations. This responsiveness translates to higher frequency oscillations of activity, contributing to faster and more local processing. Oscillations in different frequency bands may support information integration for memory, learning, and attention (Canolty and Knight, 2010).

These intuitions show how network control theory defines control based on the number of ways a region can efficiently utilize connections to dynamically guide patterns of activity to functional control targets. Of those possible network control solutions, several useful metrics assume the usage of *at least* the minimal solution theorized to be sufficient for the control problem at hand, quantify the number of solutions,

or quantify the number of hypothetically reachable control targets given particular solutions. This illustration oversimplifies the theory in many ways: for example, solutions must simultaneously account for multiple moving targets with multiple stations, the contribution of factors decay at different speeds, some factors must be used together or in sequence, and solutions are governed by additional spatial and temporal constraints. Nevertheless, the same intuitions apply to more advanced mathematics that allow network control theory to simply but powerfully model how hundreds of regions can simultaneously propagate signals across hundreds of thousands of parallel connectivity pathways over time for any measured or hypothetical control target. Remarkably, as anatomical connections change over development (Tang et al., 2017; Lim et al., 2025) and as control targets reconfigure with learning (Betzel et al., 2016; Braun et al., 2021; Zhou et al., 2023a), the brain achieves a unique dynamic reorganization of connectivity and activity for efficient network control (Kim et al., 2018).

There are a number of ways that patterns of activity in a network can be dynamically described by network control theory. This is important, because each pattern has implications for how control is enacted continuously — rather than by a static target pattern of activity — and how it influences the possibility and difficulty of future control such as switching tasks (Zhou et al., 2023a; Musslick and Bizyaeva, 2024; Zhou et al., 2025; Emonds et al., 2026). A control target can be a terminal state that may represent components of a control process, but control theory also determines the persistence and flexibility of the dynamics that lead up to the terminal state and of the dynamics that follow. Persistence is a function of stability granted by low energy, like a ball circling and ultimately resting at the bottom of a bowl. Transience and flexibility is a function of gain granted by high energy, like a ball at the top of a peak ready to roll towards any direction with just the slightest

push. The energetic efficiency of dynamics determine the representation's persistence and flexibility, or how resistant or receptive it is to changing inputs. Together, network control characterizes dynamical properties of activity, such as energetic costs, competing activity flow, energy peaks, energy valleys, timescales, and optimality of control routes. These properties open the tantalizing possibility of developing dynamical neural models that closely align with the dynamical properties of behavioral and mental control phenomena (Carver and Scheier, 2001), such as different levels of subjective effort, conflict, sensitivity to inputs, task switching, stable modes of activity, and flexibility (Szymula et al., 2020; Rouse et al., 2023; Cornblath et al., 2020; Braun et al., 2021; Luppi et al., 2024; Zhou et al., 2023a).

Applications and evidence for network control theory

Network control theory posits mathematical constructs that have been shown to be associated with psychological and neurobiological control processes, task performance, and neurodevelopment in a number of ways. For example, regions implicated in attention and control processes have been associated with high capacity for network control (Rouse et al., 2023; Gu et al., 2015; Cui et al., 2020). Individual differences in network control are correlated with individual differences in performance on cognitive control tasks probing impulsivity, executive function, and working memory (Cornblath et al., 2019, 2020; Braun et al., 2021; Cai et al., 2021). As would be expected if control is costly (Holroyd, 2025), top-down activity from frontal regions associated with goal, self-relevance, and control processes uses more control energy than the bottom-up activity of sensory regions (Parkes et al., 2022). The amount of cognitive effort demanded by working memory performance and selective attention is related to individual differences in control predicted by network control theory (Cornblath et al., 2020; Braun et al., 2021; Zhou et al., 2023a), and the network control stability of functional levels of activity for working memory is modulated by dopamine signaling at prefrontal regions (Braun et al., 2021; Cools and D'Esposito, 2011). As would be expected if excessively costly control is less likely to happen, transitions to neural states predicted to be difficult due to their costly control energy demands tend to have reduced probability of occurrence (Weninger et al., 2022; Cornblath et al., 2020; Liu et al., 2026) and have reduced frequency (Ceballos et al., 2025). As would be expected if control that is costly feels subjectively effortful, neural states predicted to be difficult due to their high control energy involve more demanding cognitive tasks (Braun et al., 2021; Zhou et al., 2023a; Saberi et al., 2024). Finally, the capacity for network control increases with age in conjunction with known periods of neurodevelopment for executive function (Tang et al., 2017; Cornblath et al., 2020; Cui et al., 2020; Lim et al., 2025). Comparatively, humans have a more efficient organization of anatomical connectivity for network control than *Drosophila* and mice (Kim et al., 2018).

Control energy is a mathematical construct centered on activity change, maintenance, and propagation, and as such, it has been associated with myriad aspects of neural signaling, including dopamine (Braun et al., 2021), serotonin (Singleton et al., 2021), GABA (Mahadevan et al., 2021), and metabolic (He et al., 2021; Ceballos et al., 2025) signaling. Network control metrics explain the spatial distribution of the genetic expression of excitatory and inhibitory neurotransmitter receptors that have been proposed to support different forms of cognitive control, including dopaminergic, noradrenergic, cholinergic, and serotonergic receptors, which are required to enact diverse neural dynamics for different cognitive tasks (Cools, 2008, 2015; Shine et al., 2019; Westbrook et al., 2020; Cools and Arnsten, 2022; Luppi et al., 2024). Together, network control theory offers a mathematical account of cognitive control as an expression of the fundamental architecture of the brain, coordinating the kind, amount, location, and timing of top-down signals to engage activity that is functional for the control tasks at hand. Just as the perception, valuation, and actions of cognitive control operate through dynamic feedback loops, anatomical connectivity itself forms recurrent loops and hierarchically nested hubs that support the efficient propagation of control signals—control loops all the way down.

Limitations and tensions of network control theory

Network control theory has several limitations. First, the theory adopts some limitations of psychological models when incorporating the same control targets as the evoked neural representations of control. These include limitations about what part of a control process the control target is supposed to represent as well as the types of goals embodied in those targets. However, network control metrics are the product of many ways in which activity evolves to a final state, not only of the terminal state itself. The theory is not wedded to any singular terminal target but the dynamics leading to any known and yet unknown targets that can be multiple realizations of control processes (Badre, 2020; Luppi et al., 2024).

Second, network control theory is currently more biologically reductive than existing psychological, computational, and neuroscience models (Badre, 2020), but it need not be in the future. Psychological theory speaks more directly to everyday control problems than the neat mathematical solutions for brain dynamics that network control theory presently offers. A preference for functional and algorithmic explanations over ones about neural implementation coheres with the goals of behavioral, cognitive, and computational scientists (Marr, 1982). Indeed, control behavior is not just the function of deterministic input–output operations of physical machinery (Wiener, 1919). Control behavior also cannot be reduced to a fully specified and task-specific set of coarse goals, finer plans, and granular actions according to iterative feedback (Carver and Scheier, 1982; Cooper and Shallice, 2000; Botvinick and Plaut, 2004; Cooper and Shallice, 2006; Holroyd et al., 2018). Cognitive control is biopsychosocial, involving the interactions within organisms just as much as with their environment and others (Dayan, 2012; Gomez-Marín and Ghazanfar, 2019; Munakata and Michaelson, 2021; Hofmann, 2024). Embracing a plurality of different biopsychosocial goals, which lead to seemingly incommensurable approaches, is where the network approach has great potential (Liu et al., 2012). To this end, network control has already been applied across levels of analysis to psychological state and psychopathological symptom networks (Henry et al., 2022b; Stocker et al., 2023). Future work could, for example, use multilayer networks to model biological, psychological, and social dynamics generated by existing cognitive computational models within the network control theory approach.

Third, network control theory can seem both too simple by modeling neural dynamics as a linear system and too complex by overlapping with the simpler network metrics of hubs. The assumption of linear dynamics improves interpretability at the cost of biophysical accuracy, allowing for formal predictions about signal flow that can be transparently translated to the additive and multiplicative contributions of particular regions and the strength of their connections in the brain. Linearity makes it mathematically clear, for example, that network control is strongly intertwined with some prior network metrics by definition, such as the communicability of signals based on the strength of anatomical connections and their resulting contribution to the reachability of control targets (Chen, 1984; Cowan et al., 2012; Betzel et al., 2016; Cole, 2017; C. Gratton et al., 2018; Patankar et al., 2020; Becker et al., 2020). Indeed, it has long been argued that control is a function of communication (Ashby, 1952, 1956; Wiener, 1919), but not that it is merely communication or only a property of communication pathways (Rubinov, 2022). Beyond the communicability of control signals, both living organisms and machines regulate behavior towards control targets that change over time through continued interaction and according to diverse contexts. Taken together, control targets and architectures determine the cost of network control, when such costs are excessively large, and precisely what control points contribute to those costs (including hubs but also other key regions often left unconsidered). Network control theory adds conceptual and computational tools to integrate and inform complex spatiotemporal interactions of measurement, stimulation, and perturbation (Shenoy and Kao, 2021), is predictive of more complex non-linear models of

neural dynamics (Muldoon et al., 2016; Kim and Bassett, 2020; Nozari et al., 2020), and links the ease of information flow to the efficiency, direction, and localization of control (Zhou et al., 2022b; Parkes et al., 2022). However, linear assumptions, and the consequent mathematical form of control energy, can come at the cost of both biophysical and computational richness (Cohen et al., 1990; Botvinick et al., 2001; O'Reilly and Frank, 2006; Herd et al., 2014; Buss and Spencer, 2014; O'Reilly et al., 2016). Three promising next steps could be applying network control theory to non-linear computational models in order to provide a complementary explanation for what makes an emerging module of computational units become specialized for control during learning (Yang et al., 2019; Zhou et al., 2022a; Suárez et al., 2024), improving accuracy by using non-linear methods for determining the expected natural flow of activity prior to applying network control theory (Brunton et al., 2016; Durstewitz et al., 2023; Brenner et al., 2024), and developing new constraints to optimal control trajectories guided by self-organized targets from the functional demands of perception-action loops beyond the spatial and energetic constraints already built into control theory models (Betzel et al., 2016; Dey and Bugg, 2021; Kim et al., 2025).

3. Opportunities for expanding, formalizing, and integrating cognitive control constructs

How network control theory contributes to the psychological understanding of cognitive control

Network control theory helps synthesize many key ideas in the neuroscience of cognitive control in a precise and mathematically coherent account. For example, it synthesizes the distinction and balance between automatic and controlled activity in service of reaching task-specific activity patterns (Cohen et al., 1990); the kind, magnitude, and location of guided activation needed for concurrent and parallel control signals to bias top-down and bottom-up systems towards functional target states (Desimone et al., 1995; Miller, 2000; Badre, 2008); the importance of multiple hierarchically structured control hubs (Cole, 2017; C. Gratton et al., 2018; Badre and Nee, 2018); the importance of recurrent connectivity in maintaining stable control representations (Rougier et al., 2005; Botvinick and Cohen, 2014); the neurodevelopment of control (Luna et al., 2015; Marek et al., 2015; Crone and Steinbeis, 2017); the physical costs of control (Shenhav et al., 2013; Cools, 2015; Lieder et al., 2018; Westbrook et al., 2020); and a general framework for feedback control across levels of analysis (Carver and Scheier, 1982; Wiener, 2019; Powers and Powers, 1973; Miller et al., 1960).

In addition, the extant network control theory literature advances our understanding of cognitive control in several key ways. First, network control theory and conventional brain mapping approaches converge in identifying which regions and networks are most important (Gu et al., 2015; Cui et al., 2020) and how their neurodevelopment may support executive control (Gu et al., 2015; Tang et al., 2017; Cornblath et al., 2019; Lim et al., 2025). Second, several predictions follow from the theory about when and how much control is required given the difficulty of a control task, the probability of activity patterns, resilience to brain damage or disruption, and the effects of perturbations or stimulation (Eisenreich et al., 2017; Yan et al., 2017; Towlson et al., 2018; Cornblath et al., 2020; Weninger et al., 2022), providing a useful theoretical testbed for neurostimulation, neurofeedback, and cognitive behavioral strategies. In this way, network-based theories can guide new investigation into regions underappreciated by prior approaches (Cole, 2017; Yan et al., 2017; Towlson et al., 2018). Third, the approach is not limited to human psychology, neurobiology, and behavior. Less dependent on the values, brain areas, and functions unobserved in other species, network control can also explain control, cognitive flexibility, attention, and learning in non-human primates (Szymula et al., 2020; Rouse et al., 2023), mice (Brynildsen et al., 2020), and *C. elegans* (Yan et al., 2017; Towlson et al., 2018). Fourth,

this approach can provide better empirical predictions of behavioral and clinical variability beyond simpler metrics describing local activity and connectivity (Yan et al., 2017; Stiso et al., 2019; Parkes et al., 2021). For example, network control theory can improve understanding of symptoms across the psychosis spectrum (Zöller et al., 2021; Parkes et al., 2021; Mahadevan et al., 2021; Dimulescu et al., 2021), depression (Kenett et al., 2018; Hahn et al., 2021, 2023; Emonds et al., 2026; Zhou et al., 2025; Liu et al., 2026), attention-deficit/hyperactivity disorder (Henry et al., 2022a), substance use (Brynildsen et al., 2020; Zhou et al., 2023a), bipolar disorder (Jeganathan et al., 2018; Wang et al., 2022), and epilepsy (Scheid et al., 2021; He et al., 2021; Chari et al., 2022). Treatments can be modeled and understood using network control theory, including pharmacological interventions (Singleton et al., 2021; Mahadevan et al., 2021), neurostimulation (Stiso et al., 2019; Beynel et al., 2020; Scheid et al., 2021; Fang et al., 2022; Wilmskoetter et al., 2022), and psychological intervention (Zhou et al., 2023a; Stocker et al., 2023). As such, the approach offers unique conceptual and empirical advantages beyond previous network measures of circuit structure and function (Rubinov, 2022; Badre, 2020).

How the psychological understanding of cognitive control contributes to network control theory

The psychology of cognitive control contributes to network control theory new kinds of behaviors that require control, how those behaviors dynamically change, how they are integrated into daily life, and different kinds of control processes or mental representations. In short, psychological approaches reveal new control targets and interpretations of network control's mathematical abstractions.

First, psychology can enrich the interpretation of control theory parameters, such as the time horizon, cost function variables, and the locations of energy input. For example, goals are hierarchical and are construed at differing timescales with differing abstractness versus concreteness (Carver and Scheier, 1982; Powers and Powers, 1973; Braver et al., 2014). This understanding motivates the design of control inputs to maintain or retrieve goal representations, over long or short time horizons, located at regions that represent more abstract or concrete information. Incongruity between choices and goals can prolong decision processes from conflict and opportunity cost representations (Bugg et al., 2008; Frömer et al., 2019; Bustamante et al., 2021; Lee and Sewell, 2024), suggesting that behavior is guided by cost functions with functional and representational constraints beyond the spatial and energetic ones already built into control theory models (Betzel et al., 2016; Dey and Bugg, 2021; Kim et al., 2025). Second, psychological and cognitive neuroscience research has described multiple sources of feedback that can influence the magnitude and location of control inputs, including feedback from regions processing stop signals, expected value, prediction errors, interoceptive signals, arousal, motivational needs, and emotions. This expanded suite of feedback signals could dampen, amplify, or prolong top-down signals from cognitive control and attention regions (Hasselmo, 2005; Thayer et al., 2009; Barrett and Simmons, 2015; Inzlicht and Berkman, 2015; Baiano et al., 2021; Sennesh et al., 2022; Shenhav, 2024; Zhang et al., 2025), and beyond the brain to the body (Thayer et al., 2009; Barrett and Simmons, 2015; Baiano et al., 2021; Sennesh et al., 2022). The regions and neurotransmitters that have been associated with the allocation of control energy overlap with those related to mental fatigue, value, effort, the cost of effort, conflict, and stop signaling (Shine et al., 2019; Braun et al., 2021; Zhou et al., 2023a; Luppi et al., 2024; Zhou et al., 2025), suggesting further potential characterizations of control energy (Shenhav et al., 2016; Randles et al., 2017; Berkman et al., 2017; Kool and Botvinick, 2018; Kok, 2022). Third, cognitive neuroscience research shows that ongoing spontaneous activity is not merely noise to be overtaken by control input but is often characteristic of default-mode network processes including prospective and episodic memory, thoughts about the self, and social reasoning (Spreng and Grady, 2010;

Koban et al., 2021; Menon, 2023). New constraints could be added to optimized control trajectories to prolong some functional aspects of prior activity or to minimize the cost of returning. Fourth, goal systems theory, social networks, and new proposals of relational reasoning as a component process of control motivate multilayer network control of interconnected brain regions, goals, needs, motivations, and other people to more directly speak to everyday individual and collective control behaviors (Diamond, 2013; Kruglanski et al., 2015; Srivastava et al., 2021; Falk and Bassett, 2017; Hofmann, 2024; Bunge, 2024).

Future directions

“The examples we used came mostly from domains of achievement and instrumental activity. However, the model is not just about achievement related affect. Those domains simply provide easy illustrations of the logic. The model is intended to apply to all goal-directed behavior. This includes attempts to attain goals that are amorphous and poorly specified, and for which constraining rates of progress is not easy. It includes goals for which the idea of rates of progress might at first seem odd. Human goals such as developing and maintaining a sound relationship, being a good [parent], dealing honorably and graciously with acquaintances, seeing someone you care about experience happiness and fulfillment, having a full and rich life, even becoming immersed in the flow of fictional lives in a novel or film are amenable to analysis in these terms. These are all qualities of human experience toward which people try to move, goals that evolve or recur across time, as do most goals underlying human action”.

[— Carver and Scheier, 2001]

Toward a new taxonomy of goals: neural bases and conceptual expansion How could any one goal be represented, given a vast universe of possible goals? If goals are attentional templates, task-relevant working memory chunks, or memory schemas, they may not have the rapid flexibility and efficiency necessary to integrate and update a wide variety of changing goals — more like moving targets than checkpoints — which draw from long-term memory, needs, and motivations. Network control theory highlights the theoretical importance for control from multiple regions that represent goals and structured memories, including the ventromedial prefrontal cortex, orbitofrontal cortex, and hippocampus (Wilson et al., 2014; Schuck et al., 2016; Mack et al., 2020). These regions may rapidly represent goals as vectors that encode direction, magnitude, timescale, and abstraction (Tolman, 1951; Lewin, 1936; Kelemen and Fenton, 2016; Bellmund et al., 2018; Brunec et al., 2018; Chung et al., 2021; Park et al., 2025), in support of both spatial navigation and more abstract goal-oriented behavior. The vectorial targets may be instances of basic needs, motivations, and drives (Atkinson, 1957; White, 1959; Bandura, 1977; Higgins, 2011) that underlie goal selection (Molinaro and Collins, 2023) and shape signals to regions implementing working memory. Applied to cognitive control, these perspectives echo the “life space”, cognitive map, and vector field metaphor of goals in psychology, with non-spatial elements such as semantic, emotional, social, reward, or motivational features particularly underutilized due to limitations in measurement and modeling tools (Tolman, 1951; Lewin, 1936; Giallanza et al., 2024). Natural language processing and large language models can now be used to represent complex hierarchies of control problems, needs, and goals as a kind of semantic meaning vector (Pistilli et al., 2024; Giallanza et al., 2024; Bhatia et al., 2025; Tamir et al., 2025). With the tools of network control theory, it is possible to scale beyond the narrow assumption of isolated goals to model the dynamics of more ecologically plausible constellations of interconnected goals and motivations (Kruglanski and Kopetz, 2009; Kruglanski et al., 2018; Henry et al., 2022b; McGowan et al., 2023; Werner and Berkman, 2024).

Social self-regulation and goal-setting through emotion, motivation, mindsets, and narratives. Goals are dynamic rather than

static terminal states, and goal pursuit is interwoven with emotion, motivation, mindsets, and narratives, influencing beliefs about what and how goals can be achieved (Rotter, 1966; Deci and Ryan, 2000; Higgins, 2005; Dweck and Yeager, 2019; Dweck, 2017; Oyserman et al., 2017; Zacks, 2020; Molinaro and Collins, 2023; Werner and Berkman, 2024; Shenhav, 2024; Chen and Bornstein, 2024; Chu et al., 2024). Beyond an individual’s personal goals, some goals have social origins and goal pursuit can be a collective behavior (Falk and Bassett, 2017; Hofmann, 2024). Moving beyond static trait measures, dynamic modeling of individual emotional and motivational states using dense real-world ecological momentary assessment can improve our understanding of cognitive control in context (McGowan et al., 2023; Schurr et al., 2024; Lee et al., 2025; Tamir et al., 2025). For example, autonomous rather than instructed motivation or goal selection may facilitate goal pursuit and perceived ease by evoking efficient usage of control energy that temporarily stabilizes the focus of the pursuit (Werner and Berkman, 2024; Molinaro and Collins, 2023). This interconnectivity of domains suggests the need for network representations to track the complex influence among different modalities, combining measurements of psychological states from ecological momentary assessment, performance on multiple tasks, and fMRI within a single framework. Multi-layer network models offer a way to simultaneously represent such neural and psychological influences, capturing how goals and emotions co-regulate behavior across different people, timescales, and contexts (Falk and Bassett, 2017; Srivastava et al., 2021; Henry et al., 2022b; Stocker et al., 2023).

Dynamic, biologically constrained computational models of control. Recurrent neural networks and other computational models allow researchers to investigate the learning and adaptation of control strategies across tasks, providing insight into how structural connections adapt and give rise to behavioral outputs (Cohen et al., 1990; Miller et al., 2003; Rougier et al., 2005; Herd et al., 2014; Song et al., 2016; Musall et al., 2019; Yang et al., 2019; Jaffe et al., 2023; Suárez et al., 2024). Network control theory could be leveraged to study how the cost of control shapes the geometry of task representations (Badre et al., 2021; Achterberg et al., 2023), influencing decision-making under energetic and temporal constraints (Shenoy and Kao, 2021), as well as the conditions that explain why local versus distributed control modules emerge from the communicability of neural networks as they learn (Eisenreich et al., 2017; Yang et al., 2019; Zhou et al., 2022a; Achterberg et al., 2023).

Timeliness of interdigitation. These approaches point toward both theory-rich and ecologically grounded investigations of cognitive control. Now is a momentous period when there is ample neural data at the cellular, genetic, and regional levels, across childhood, adolescence, and in aging, with continuous tracking of behavior, rich methods of disentangling psychological subprocesses using computational models of behavior, and new methods for querying cognitive and emotional states at scale. The observation that this is more data than researchers know what to do with is often used as a call for more theory. Here, we have described one such theory that has accumulated a wide range of evidence in neuroscience, psychology, physics, and bioengineering. We have suggested some possible pathways to bridge the constructs. Towards this end, there are unique opportunities to study cognitive control naturalistically, and to better understand the state dependence thereof in a much more ecologically valid fashion.

A major goal of research is to develop multi-level models and biopsychosocial understanding, because these are more robust, capture more data, speak to diverse goals across disciplines, and offer multiple pathways for intervention. In this review, we have shown how psychological and cognitive neuroscience models of control provide the strongest constraints at the behavioral level — by specifying what kinds of behavior count as instances of control and what kinds of goals might one try to pursue — but the weakest constraints on the brain level. By contrast, network control theory currently provides stronger constraints on the physical level of the brain than it does on the behavioral level.

Combining complementary aspects of each could provide the strongest currently available means of theory and modeling across levels of analysis.

Conclusion. The extant network control theory literature undergirds, synthesizes, prunes, and expands cognitive neuroscience theories of control. For example, network control undergirds and synthesizes the role of distributed regions in guided activation via dynamic feedback loops, prunes cultural and moral assumptions about power or the right kinds of goals, and expands the theoretical scope of controllers and control targets relevant to semantic, emotional, social, learning, memory, and motivational processes. Network control theory is within its first decades of investigation, and in the course of expansion and formalization, it may become clear an entirely different model provides a better fit to psychological and neural data. New measurement modalities may revolutionize how we implement state estimation. The limits of connectomic approaches may not bend to theoretical and numerical approaches to modeling. Practical demands for implementation in medical devices or artificial intelligence may necessitate non-linear rather than linear methods. Psychological models of cognitive control may prove more relevant than neural models to the design of personal interventions, scalable measurement, societal goals, structural changes to public policy, economic systems, and cultural norms. Nonetheless, network control theory offers useful tools to intuitively understand cognitive control as a cohesive dynamic and distributed neural process.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank Dr. Aaron Bornstein for helpful feedback on earlier versions of this manuscript. This research was supported by the Center for Curiosity and was sponsored by the Army Research Office, accomplished under Grant W911NF-18-1-0244. DZ acknowledges support from the George E. Hewitt Foundation for Medical Research. KO was additionally supported by the Center for Brain Mind and Society, ARO grant W911NF-19-1-0411, and grant R01AA023653 from NIAAA. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Office or the US government. The US government is authorized to reproduce and distribute reprints for government purposes notwithstanding any copyright notation herein.

Appendix

4.1. Fig. 1 methods

Fig. 1 is based on a previously published review in the digital humanities (Burman et al., 2015), which created a concept network for the psychological construct of self-regulation from linked terms in the American Psychological Association Thesaurus of Psychological Index Terms® (Tuleya, 2007). These terms characterize the semantics of psychological science, defining what the words used by psychologists mean to other psychologists (VandenBos, 2007, 2009; Tuleya, 2007).

Following the guidance of the procedure detailed in this previously published review (Burman et al., 2015), we began a search with two terms “cognitive control” and “self-regulation” in the June 2025 edition of the APA Thesaurus (American Psychological Association, 2023). These serve as first-level seed terms. We then obtained the hierarchy of concepts linked to the first-level seed terms to generate a second-level

of 13 new seed terms. The second-level terms included: cognitive flexibility, executive function (higher order processes), executive functioning measures, set shifting (attentional set shifting, cognitive set shifting), task switching, agency, emotional regulation (affect regulation, expressive suppression), neurofeedback, self-control (willpower), self-management, self-monitoring (self-observation), self-monitoring (personality), and self-regulated learning. Finally, we obtained concepts linked to the second-level terms to generate a third-level of 38 terms. This procedure produced 67 terms and their associated definitions (range: 1 to 82 words; mean 19 ± 14 words). The prior work goes one level deeper to fourth-level terms, which is useful because constructs like “goals” and “values” live at that level, but we chose to stop at terms two links away for concision—the sheer breadth of indirectly related constructs dilutes the original meaning of cognitive control or self-regulation. For the few terms without a definition, we used their list of linked terms as a substitute.

Here, our methods diverge from those of the prior paper in order to use recently developed natural language processing and clustering techniques. To cluster the terms and visualize a network of term similarity, we first sought to normalize the number of words used in each term’s definition. To do so, we augment the definitions by a large-language model. Recent work has relied on GPT-4 to write definitions of psychological terms in order to study similarity and ambiguity among constructs (Wulff and Mata, 2025). Following their example, we prompt for 100- or 150-word definitions from GPT-4o via the API using the prompt: “You are an expert in psychology and personality theory. Here is a technical dictionary definition of the construct ‘{label}’: ‘{definition}’. Expand this into a {length}-word version that retains its scientific accuracy while adding conceptual richness and clarity for a research audience. Use formal psychological language”.

Finally, we applied a topic clustering method using a hierarchical stochastic block model (Peixoto, 2014). This method detects community structure in a term-by-definition co-occurrence network (Gerlach et al., 2018). We construct the bipartite network by defining a biadjacency matrix where rows are the psychological terms and columns are the words used in the definitions. Edges represent the number of times a word appears in a term’s definition.

Using a hierarchical stochastic block model, we can cluster definitions and terms into blocks (topics) without needing to predefine the number of topics or rely on a prior probability distribution like in Latent Dirichlet Allocation. Each topic corresponds to a block of words, forming a distribution over words based on their co-occurrence across documents. Similarly, terms are grouped into blocks that share similar word usage, yielding a distribution over terms for each definition word. These distributions emerge naturally from the block structure inferred. Finally, we visualize the term-by-definition bipartite network and use a unique color for each inferred block.

4.2. Fig. 2 methods

Fig. 2 uses the data and results from Figures 2, 3, and 4 in Eisenberg et al. (2019). After downloading their publicly available data, we followed their procedure to process individual performance on 129 task and 64 survey measures ($n = 560$). We used a 560×193 participant-by-measure matrix to create a 193×193 measure-by-measure similarity matrix by calculating the pairwise partial correlation between every pair of measures, controlling for the effect of other measures.

This structure can be visualized as a fully connected graph, but topology is difficult to ascertain from such a densely connected network. To identify dependencies between the measures, graphical lasso (scikit-learn) applies L1 regularization ($\alpha = 0.15$) to make many entries zero and reduce noisy correlations, making the network more interpretable (Friedman et al., 2008; Pedregosa et al., 2011). This returns a 193×193 measure-by-measure similarity matrix, which we threshold to remove very small correlations $|r| < 0.05$. We obtain an adjacency matrix similar to the one visualized in Figure 2 in Eisenberg et al.

(2019). Each node is a measure's dependent variable and each edge is the partial correlation between measurement variables.

Here, our methods diverge from those in the prior work (Eisenberg et al., 2019). To find and visualize community structure in this sparse graph, we perform clustering by using a stochastic block model implemented in `minimize_nested_blockmodel_dl` by the `graph-tool` library (Peixoto, 2014). This community detection approach relies on minimizing a probabilistic description length objective to reveal nested groupings in the network. In contrast, the force-directed layout used in the original figure relies on spatial and visual heuristics, rather than statistical or generative structure. The community detection procedure reveals that the 193×193 matrix is best modeled by 5 communities, naturally separating survey measurements into two interconnected communities and task measurements into 3 interconnected communities. As in the prior work, these regularization techniques reveal that the task measure communities are largely unrelated to the survey measure communities. However, this may be a result of the application of moderate regularization or the extensive abbreviation of the task durations for the sake of practical experimental implementation, larger sample size, and coverage of measurements.

Finally, we visualize the 193×193 matrix as a network and color its nodes according to how the variable that the node represents loads onto independent latent factors obtained from the exploratory factor analysis reported in Eisenberg et al. (2019). The 129 task variables loaded onto 5 factors in a 129×5 loading matrix with the following factors: speeded information processing, strategic information processing, perception/response, caution, and discounting. The 64 survey measures loaded onto 12 factors in a 64×12 loading matrix with the following factors: sensation seeking, emotional control, mindfulness, impulsivity, reward sensitivity, goal-directedness, risk perception, eating control, ethical risk-taking, social risk-taking, financial risk-taking, and agreeableness. The task and survey factor matrices contain loadings λ that characterize the strength and direction of the relationship between the variable and an underlying latent factor.

For each node of the network, we determined the factor with the maximum magnitude loading $|\lambda|$ and color nodes with a unique tone based on their factor names. For each community, we depict the names of the variables corresponding to the community's nodes using word clouds. The size of a word is proportional to its frequency within its community (phrases and names are treated as a single combined word, and then separated after counting their frequency for visualization).

4.3. Fig. 3 methods

To create Fig. 3, we obtained bibliometric data by performing a literature search on Web of ScienceTM for the keywords, “cognitive control computational”. This search resulted in 308 articles. We saved the title, keywords, and abstract in BibTeX format.

Using similar methods as for Fig. 1, we again performed topic clustering with a hierarchical stochastic block model. The first step is constructing an article-by-word co-occurrence network (Gerlach et al., 2018). This is a biadjacency matrix where rows are articles and columns are the words used in the keywords or abstracts. Edges represent the number of times a word appears in an article.

Several manual and automatic steps were taken for natural language processing. We manually defined and replaced synonymous terms. For example, “addiction” replaced the phrases “substance abuse”, “substance dependence”, “substance use disorders”, and “craving and relapse”. Known phrases were treated as a single word when calculating frequency. Automatic processing involved stemming and lemmatizing words (e.g., “studies” $\rightarrow$ “study”), as well as removing stop words (e.g., “the”, “is”, “and”, “in”, and “of”).

Using a hierarchical stochastic block model, we cluster words and articles into blocks (topics). Each topic corresponds to a block of words, forming a distribution over words based on their co-occurrence across articles. Similarly, terms are grouped into blocks that share similar

word usage across articles, giving a distribution over terms for each definition word. This data yielded multiple nested layers of communities, where nodes are grouped into blocks at the lowest level, and these blocks themselves are grouped into higher-level blocks. The block hierarchy is depicted as a tree structure in blue. Finally, we visualize the article-by-word bipartite network, using a unique color for each inferred block, and we only visualize the strongest 1000 article-word co-occurrences.

4.4. Fig. 5 methods

To create Fig. 5, we reproduced visualizations from Zhou et al. (2023a) and Zhou et al. (2022b).

4.5. Fig. 6 methods

To create Fig. 6, we query Neurosynth for the term “cognitive control” (Yarkoni et al., 2011). We download the association test maps, which contain voxels that quantify the probability of cognitive control reported in studies, given activation at specific voxel coordinates. These voxel values are z -scores from a two-way ANOVA testing for the presence of a non-zero association between term use and voxel activation, controlling for multiple comparison with a false discovery rate (FDR) criterion of $q < .01$. We parcellate the voxels into brain regions according to the Glasser atlas (Glasser et al., 2016) and visualize the maximum z -score of the voxels within that region so long as it surpasses a threshold of $z > 3.3$ (corresponding to $p < 0.001$). Hub and recurrence visualizations are reproduced from Refs. Zhou et al. (2022b, 2023b).

4.6. Citation diversity statement

Recent work in several fields of science has identified a bias in citation practices such that papers from women and other minority scholars are under-cited relative to the number of such papers in the field (Mitchell et al., 2013; Dion et al., 2018; Caplar et al., 2017; Maliniak et al., 2013; Dworkin et al., 2020; Bertolero et al., 2020; Wang et al., 2021; Chatterjee and Werner, 2021; Fulvio et al., 2021). Here we sought to proactively consider choosing references that reflect the diversity of the field in thought, form of contribution, gender, race, ethnicity, and other factors. First, we obtained the predicted gender of the first and last author of each reference by using databases that store the probability of a first name being carried by a woman (Dworkin et al., 2020; Zhou et al., 2020). By this measure (and excluding self-citations to the first and last authors of our current paper), our references contain 11.07% woman(first)/woman(last), 12.89% man/woman, 16.38% woman/man, and 59.65% man/man. This method is limited in that (a) names, pronouns, and social media profiles used to construct the databases may not, in every case, be indicative of gender identity and (b) it cannot account for intersex, non-binary, or transgender people. Second, we obtained predicted racial/ethnic category of the first and last author of each reference by databases that store the probability of a first and last name being carried by an author of color (Ambekar et al., 2009; Sood and Laohaprapanon, 2018). By this measure (and excluding self-citations), our references contain 7.26% author of color (first)/author of color(last), 10.61% white author/author of color, 20.06% author of color/white author, and 62.06% white author/white author. This method is limited in that (a) names and Florida Voter Data to make the predictions may not be indicative of racial/ethnic identity, and (b) it cannot account for Indigenous and mixed-race authors, or those who may face differential biases due to the ambiguous racialization or ethnicization of their names. We look forward to future work that could help us to better understand how to support equitable practices in science.

References

- Achterberg, J., Akarca, D., Strouse, D., Duncan, J., Astle, D.E., 2023. Spatially embedded recurrent neural networks reveal widespread links between structural and functional neuroscience findings. *Nat. Mach. Intell.* 5 (12), 1369–1381.
- Agrawal, M., Mattar, M.G., Cohen, J.D., Daw, N.D., 2022. The temporal dynamics of opportunity costs: A normative account of cognitive fatigue and boredom. *Psychol. Rev.* 129 (3), 564.
- Alexander, W.H., Brown, J.W., 2011. Medial prefrontal cortex as an action-outcome predictor. *Nature Neurosci.* 14 (10), 1338–1344.
- Ambekar, A., Ward, C., Mohammed, J., Male, S., Skiena, S., 2009. Name-ethnicity classification from open sources. In: *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. pp. 49–58.
- Amer, T., Campbell, K.L., Hasher, L., 2016. Cognitive control as a double-edged sword. *Trends Cogn. Sci.* 20 (12), 905–915.
- American Psychological Association, 2023. *APA thesaurus of psychological index terms*. <https://www.apa.org/pubs/databases/training/thesaurus>. Accessed via PsycINFO; provides controlled vocabulary for psychological concepts.
- Arnsten, A.F., Rubia, K., 2012. Neurobiological circuits regulating attention, cognitive control, motivation, and emotion: disruptions in neurodevelopmental psychiatric disorders. *J. Am. Acad. Child & Adolesc. Psychiatry* 51 (4), 356–367.
- Aron, A.R., 2007. The neural basis of inhibition in cognitive control. *The Neuroscientist* 13 (3), 214–228.
- Aron, A.R., Herz, D.M., Brown, P., Forstmann, B.U., Zaghoul, K., 2016. Fronto-subthalamic circuits for control of action and cognition. *J. Neurosci.* 36 (45), 11489–11495.
- Aron, A.R., Poldrack, R.A., 2006. Cortical and subcortical contributions to stop signal response inhibition: role of the subthalamic nucleus. *J. Neurosci.* 26 (9), 2424–2433.
- Aron, A.R., Robbins, T.W., Poldrack, R.A., 2014. Inhibition and the right inferior frontal cortex: one decade on. *Trends Cogn. Sci.* 18 (4), 177–185.
- Asaad, W.F., Rainer, G., Miller, E.K., 2000. Task-specific neural activity in the primate prefrontal cortex. *J. Neurophysiol.* 84 (1), 451–459.
- Ashby, W., 1952. *Design for a Brain: The Origin of Adaptive Behaviour*. Springer Science & Business Media.
- Ashby, W.R., 1956. An introduction to cybernetics.
- Atkinson, J.W., 1957. Motivational determinants of risk-taking behavior. *Psychol. Rev.* 64 (6p1), 359.
- Avena-Koenigsberger, A., Masic, B., Sporns, O., 2018. Communication dynamics in complex brain networks. *Nature Rev. Neurosci.* 19 (1), 17–33.
- Baddeley, A., 2002. Fractionating the central executive. *Princ. Front. Lobe Funct.* 246–260.
- Badre, D., 2008. Cognitive control, hierarchy, and the rostro-caudal organization of the frontal lobes. *Trends Cogn. Sci.* 12 (5), 193–200.
- Badre, D., 2020. Brain networks for cognitive control: four unresolved questions. In: *Intrusive Thinking across Neuropsychiatric Disorders: From Molecules to Free Will*. pp. 203–228.
- Badre, D., 2022. *On Task: How Our Brain Gets Things Done*. Princeton University Press.
- Badre, D., Bhandari, A., Keglovits, H., Kikumoto, A., 2021. The dimensionality of neural representations for control. *Curr. Opin. Behav. Sci.* 38, 20–28.
- Badre, D., Hoffman, J., Cooney, J.W., D'Esposito, M., 2009. Hierarchical cognitive control deficits following damage to the human frontal lobe. *Nature Neurosci.* 12 (4), 515–522.
- Badre, D., Nee, D.E., 2018. Frontal cortex and the hierarchical control of behavior. *Trends Cogn. Sci.* 22 (2), 170–188.
- Badre, D., Poldrack, R.A., Paré-Blagoev, E.J., Insler, R.Z., Wagner, A.D., 2005. Dissociable controlled retrieval and generalized selection mechanisms in ventrolateral prefrontal cortex. *Neuron* 47 (6), 907–918.
- Badre, D., Wagner, A.D., 2007. Left ventrolateral prefrontal cortex and the cognitive control of memory. *Neuropsychologia* 45 (13), 2883–2901.
- Baiano, C., Santangelo, G., Senese, V.P., Di Mauro, G., Lauro, G., Piacenti, M., Conson, M., 2021. Linking perception of bodily states and cognitive control: the role of interoception in impulsive behaviour. *Exp. Brain Res.* 239 (3), 857–865.
- Bandura, A., 1977. Self-efficacy: toward a unifying theory of behavioral change. *Psychol. Rev.* 84 (2), 191.
- Barch, D.M., Culbreth, A., Sheffield, J., 2018. Systems level modeling of cognitive control in psychiatric disorders: A focus on schizophrenia. In: *Computational Psychiatry*. Elsevier, pp. 145–173.
- Barrett, L.F., Simmons, W.K., 2015. Interoceptive predictions in the brain. *Nature Rev. Neurosci.* 16 (7), 419–429.
- Bassett, D.S., Bullmore, E., 2006. Small-world brain networks. *The Neuroscientist* 12 (6), 512–523.
- Bassett, D.S., Greenfield, D.L., Meyer-Lindenberg, A., Weinberger, D.R., Moore, S.W., Bullmore, E.T., 2010. Efficient physical embedding of topologically complex information processing networks in brains and computer circuits. *PLoS Comput. Biol.* 6 (4), e1000748.
- Becker, C.O., Pequeto, S., Pappas, G.J., Preciado, V.M., 2020. Network design for controllability metrics. *IEEE Trans. Control. Netw. Syst.* 7 (3), 1404–1415.
- Bellmund, J.L., Gärdenfors, P., Moser, E.I., Doeller, C.F., 2018. Navigating cognition: Spatial codes for human thinking. *Science* 362 (6415), eaat6766.
- Berkman, E.T., Hutcherson, C.A., Livingston, J.L., Kahn, L.E., Inzlicht, M., 2017. Self-control as value-based choice. *Curr. Dir. Psychol. Sci.* 26 (5), 422–428.
- Bermúdez, J.P., Murray, S., 2024. Believe in your self-control: Lay theories of self-control and their downstream effects. *Curr. Opin. Psychol.* 60, 101879.
- Bertolero, M.A., Dworkin, J.D., David, S.U., Lloreda, C.L., Srivastava, P., Stiso, J., Zhou, D., Dzirasa, K., Fair, D.A., Kaczkurkin, A.N., Marlin, B.J., Shohamy, D., Uddin, L.Q., Zurn, P., Bassett, D.S., 2020. Racial and ethnic imbalance in neuroscience reference lists and intersections with gender. *bioRxiv*.
- Betz, R.F., Gu, S., Medaglia, J.D., Pasqualetti, F., Bassett, D.S., 2016. Optimally controlling the human connectome: the role of network topology. *Sci. Rep.* 6 (1), 30770.
- Beynel, L., Deng, L., Crowell, C.A., Dannhauer, M., Palmer, H., Hilbig, S., Peterchev, A.V., Luber, B., Lisanby, S.H., Cabeza, R., et al., 2020. Structural controllability predicts functional patterns and brain stimulation benefits associated with working memory. *J. Neurosci.* 40 (35), 6770–6778.
- Bhatia, S., van Baal, S.T., Wang, F., Walasek, L., 2025. Computational analysis of 100 K choice dilemmas: Decision attributes, trade-off structures, and model-based prediction. *Proc. Natl. Acad. Sci.* 122 (17), e2406489122.
- Blair, C., Razza, R.P., 2007. Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child Dev.* 78 (2), 647–663.
- Botvinick, M., Braver, T., 2015. Motivation and cognitive control: from behavior to neural mechanism. *Annu. Rev. Psychol.* 66 (1), 83–113.
- Botvinick, M.M., Braver, T.S., Barch, D.M., Carter, C.S., Cohen, J.D., 2001. Conflict monitoring and cognitive control. *Psychol. Rev.* 108 (3), 624.
- Botvinick, M.M., Cohen, J.D., 2014. The computational and neural basis of cognitive control: Charted territory and new frontiers. *Cogn. Sci.* 38 (6), 1249–1285.
- Botvinick, M., Plaut, D.C., 2004. Doing without schema hierarchies: a recurrent connectionist approach to normal and impaired routine sequential action. *Psychol. Rev.* 111 (2), 395.
- Boureau, Y.-L., Sokol-Hessner, P., Daw, N.D., 2015. Deciding how to decide: Self-control and meta-decision making. *Trends Cogn. Sci.* 19 (11), 700–710.
- Brandstätter, V., Bernecker, K., 2022. Persistence and disengagement in personal goal pursuit. *Annu. Rev. Psychol.* 73 (1), 271–299.
- Braun, U., Harneit, A., Pergola, G., Menara, T., Schäfer, A., Betzel, R.F., Zang, Z., Schweiger, J.I., Zhang, X., Schwarz, K., et al., 2021. Brain network dynamics during working memory are modulated by dopamine and diminished in schizophrenia. *Nat. Commun.* 12 (1), 1–11.
- Braunstein, L.M., Gross, J.J., Ochsner, K.N., 2017. Explicit and implicit emotion regulation: a multi-level framework. *Soc. Cogn. Affect. Neurosci.* 12 (10), 1545–1557.
- Braver, T.S., 2012. The variable nature of cognitive control: a dual mechanisms framework. *Trends Cogn. Sci.* 16 (2), 106–113.
- Braver, T.S., Krug, M.K., Chiew, K.S., Kool, W., Westbrook, J.A., Clement, N.J., Adcock, R.A., Barch, D.M., Botvinick, M.M., Carver, C.S., et al., 2014. Mechanisms of motivation-cognition interaction: challenges and opportunities. *Cogn. Affect. & Behav. Neurosci.* 14 (2), 443–472.
- Brenner, M., Weber, E., Koppe, G., Durstewitz, D., 2024. Learning interpretable hierarchical dynamical systems models from time series data. *arXiv preprint arXiv: 2410.04814*.
- Brune, I.K., Bellana, B., Ozubko, J.D., Man, V., Robin, J., Liu, Z.-X., Grady, C., Rosenbaum, R.S., Winocur, G., Barense, M.D., et al., 2018. Multiple scales of representation along the hippocampal anteroposterior axis in humans. *Curr. Biol.* 28 (13), 2129–2135.
- Brunton, S.L., Kutz, J.N., 2022. *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*. Cambridge University Press.
- Brunton, S.L., Proctor, J.L., Kutz, J.N., 2016. Discovering governing equations from data by sparse identification of nonlinear dynamical systems. *Proc. Natl. Acad. Sci.* 113 (15), 3932–3937.
- Brynlidsen, J.K., Mace, K.D., Cornblath, E.J., Weidler, C., Pasqualetti, F., Bassett, D.S., Blendy, J.A., 2020. Gene coexpression patterns predict opiate-induced brain-state transitions. *Proc. Natl. Acad. Sci.* 117 (32), 19556–19565.
- Bugg, J.M., Jacoby, L.L., Toth, J.P., 2008. Multiple levels of control in the stroop task. *Mem. Cogn.* 36 (8), 1484–1494.
- Bunge, S.A., 2024. How should we slice up the executive function pie? striving toward an ontology of cognitive control processes. *Mind, Brain, Educ.* 18 (1), 17–27.
- Burman, J.T., Green, C.D., Shanker, S., 2015. On the meanings of self-regulation: Digital Humanities in service of conceptual clarity. *Child Dev.* 86 (5), 1507–1521.
- Buss, A.T., Spencer, J.P., 2014. The emergent executive: A dynamic field theory of the development of executive function. *Monogr. Soc. Res. Child Dev.* 79 (2), vii.
- Bustamante, L., Lieder, F., Musslick, S., Shenav, A., Cohen, J., 2021. Learning to overexert cognitive control in a stroop task. *Cogn. Affect. & Behav. Neurosci.* 21, 453–471.
- Cai, W., Ryali, S., Pasumathy, R., Talasila, V., Menon, V., 2021. Dynamic causal brain circuits during working memory and their functional controllability. *Nat. Commun.* 12 (1), 3314.
- Canolty, R.T., Knight, R.T., 2010. The functional role of cross-frequency coupling. *Trends Cogn. Sci.* 14 (11), 506–515.
- Caplan, N., Tachella, S., Birrer, S., 2017. Quantitative evaluation of gender bias in astronomical publications from citation counts. *Nat. Astron.* 1 (6), 0141.

- Carver, C.S., Scheier, M.F., 1982. Control theory: A useful conceptual framework for personality-social, clinical, and health psychology. *Psychol. Bull.* 92 (1), 111.
- Carver, C.S., Scheier, M.F., 2001. On the Self-Regulation of Behavior. Cambridge University Press.
- Casey, B., Tottenham, N., Fossella, J., 2002. Clinical, imaging, lesion, and genetic approaches toward a model of cognitive control. *Dev. Psychobiol.: J. Int. Soc. Dev. Psychobiol.* 40 (3), 237–254.
- Cavanagh, J.F., Frank, M.J., 2014. Frontal theta as a mechanism for cognitive control. *Trends Cogn. Sci.* 18 (8), 414–421.
- Ceballos, E.G., Luppi, A.I., Castrillon, G., Sagar, M., Misis, B., Riedl, V., 2025. The control costs of human brain dynamics. *Netw. Neurosci.* 9 (1), 77.
- Chari, A., Seunarine, K.K., He, X., Tisdall, M.M., Clark, C.A., Bassett, D.S., Scott, R.C., Rosch, R.E., 2022. Drug-resistant focal epilepsy in children is associated with increased modal controllability of the whole brain and epileptogenic regions. *Commun. Biol.* 5 (1), 394.
- Chatterjee, P., Werner, R.M., 2021. Gender disparity in citations in high-impact journal articles. *JAMA Netw. Open* 4 (7), e2114509.
- Chen, C.-T., 1984. Linear System Theory and Design. Saunders college publishing.
- Chen, J., Bornstein, A.M., 2024. The causal structure and computational value of narratives. *Trends Cogn. Sci.*
- Chiu, Y.-C., Jiang, J., Egner, T., 2017. The caudate nucleus mediates learning of stimulus-control state associations. *J. Neurosci.* 37 (4), 1028–1038.
- Chu, J., Tenenbaum, J.B., Schulz, L.E., 2024. In praise of folly: flexible goals and human cognition. *Trends Cogn. Sci.* 28 (7), 628–642.
- Chung, A., Jou, C., Grau-Perales, A., Levy, E.R., Dvorak, D., Hussain, N., Fenton, A.A., 2021. Cognitive control persistently enhances hippocampal information processing. *Nature* 600 (7889), 484–488.
- Clairis, N., Lopez-Persem, A., 2023. Debates on the dorsomedial prefrontal/dorsal anterior cingulate cortex: insights for future research. *Brain* 146 (12), 4826–4844.
- Cocchi, L., Zalesky, A., Fornito, A., Mattingley, J.B., 2013. Dynamic cooperation and competition between brain systems during cognitive control. *Trends Cogn. Sci.* 17 (10), 493–501.
- Cohen, J.D., Dunbar, K., McClelland, J.L., 1990. On the control of automatic processes: a parallel distributed processing account of the Stroop effect. *Psychol. Rev.* 97 (3), 332.
- Cole, M.W., 2017. Control and connectivity: Dynamic networks in the human brain. In: *The Wiley Handbook of Cognitive Control*. Wiley Online Library, pp. 314–333.
- Cole, M.W., Laurent, P., Stocco, A., 2013. Rapid instructed task learning: A new window into the human brain's unique capacity for flexible cognitive control. *Cogn. Affect. & Behav. Neurosci.* 13, 1–22.
- Collins, A.G., Frank, M.J., 2013. Cognitive control over learning: creating, clustering, and generalizing task-set structure. *Psychol. Rev.* 120 (1), 190.
- Cools, R., 2008. Role of dopamine in the motivational and cognitive control of behavior. *The Neuroscientist* 14 (4), 381–395.
- Cools, R., 2015. The cost of dopamine for dynamic cognitive control. *Curr. Opin. Behav. Sci.* 4, 152–159.
- Cools, R., Arnsten, A.F., 2022. Neuromodulation of prefrontal cortex cognitive function in primates: the powerful roles of monoamines and acetylcholine. *Neuropsychopharmacology* 47 (1), 309–328.
- Cools, R., D'Esposito, M., 2011. Inverted-U-shaped dopamine actions on human working memory and cognitive control. *Biol. Psychiatry* 69 (12), e113–e125.
- Cooper, R., Shallice, T., 2000. Contention scheduling and the control of routine activities. *Cogn. Neuropsychol.* 17 (4), 297–338.
- Cooper, R.P., Shallice, T., 2006. Hierarchical Schemas and Goals in the Control of Sequential Behavior. American Psychological Association.
- Cornblath, E.J., Ashourvan, A., Kim, J.Z., Betzel, R.F., Ciric, R., Adebimpe, A., Baum, G.L., He, X., Ruparel, K., Moore, T.M., et al., 2020. Temporal sequences of brain activity at rest are constrained by white matter structure and modulated by cognitive demands. *Commun. Biol.* 3 (1), 261.
- Cornblath, E.J., Tang, E., Baum, G.L., Moore, T.M., Adebimpe, A., Roalf, D.R., Gur, R.C., Gur, R.E., Pasqualetti, F., Satterthwaite, T.D., et al., 2019. Sex differences in network controllability as a predictor of executive function in youth. *NeuroImage* 188, 122–134.
- Cowan, N.J., Chastain, E.J., Vilhena, D.A., Freudenberger, J.S., Bergstrom, C.T., 2012. Nodal dynamics, not degree distributions, determine the structural controllability of complex networks. *PLoS One* 7 (6), e38398.
- Crone, E.A., Steinbeis, N., 2017. Neural perspectives on cognitive control development during childhood and adolescence. *Trends Cogn. Sci.* 21 (3), 205–215.
- Cui, Z., Stiso, J., Baum, G.L., Kim, J.Z., Roalf, D.R., Betzel, R.F., Gu, S., Lu, Z., Xia, C.H., He, X., et al., 2020. Optimization of energy state transition trajectory supports the development of executive function during youth. *Elife* 9, e53060.
- Davidson, D., 2001. How is weakness of the will possible? *Essays Actions Events* 21–42.
- Daw, N.D., Niv, Y., Dayan, P., 2005. Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control. *Nature Neurosci.* 8 (12), 1704–1711.
- Dayan, P., 2012. How to set the switches on this thing. *Curr. Opin. Neurobiol.* 22 (6), 1068–1074.
- de Kloet, S.F., Bruinsma, B., Terra, H., Heistek, T.S., Passchier, E.M., van den Berg, A.R., Luchicchi, A., Min, R., Pattij, T., Mansvelder, H.D., 2021. Bi-directional regulation of cognitive control by distinct prefrontal cortical output neurons to thalamus and striatum. *Nat. Commun.* 12 (1), 1–15.
- DeCaro, M.S., Thomas, R.D., Albert, N.B., Beilock, S.L., 2011. Choking under pressure: multiple routes to skill failure. *J. Exp. Psychol. [Gen.]* 140 (3), 390.
- Deci, E.L., Ryan, R.M., 2000. The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychol. Inq.* 11 (4), 227–268.
- Deci, E.L., Ryan, R.M., 2013. Intrinsic Motivation and Self-Determination in Human Behavior. Springer Science & Business Media.
- Desimone, R., Duncan, J., et al., 1995. Neural mechanisms of selective visual attention. *Annu. Rev. Neurosci.* 18 (1), 193–222.
- Dey, A., Bugg, J.M., 2021. The timescale of control: A meta-control property that generalizes across tasks but varies between types of control. *Cogn. Affect. & Behav. Neurosci.* 21, 472–489.
- DeYoung, C.G., Krueger, R.F., 2018. A cybernetic theory of psychopathology. *Psychol. Inq.* 29 (3), 117–138.
- Diamond, A., 2013. Executive functions. *Annu. Rev. Psychol.* 64 (1), 135–168.
- Diamond, A., Goldman-Rakic, P., 1986. Comparative development in human infants and infant rhesus monkeys of cognitive functions that depend on prefrontal cortex. In: *Society for Neuroscience Abstracts*, vol. 12, (no. 742), p. 2.
- Dimulescu, C., Gareayaghi, S., Kamp, F., Fromm, S., Obermayer, K., Metzner, C., 2021. Structural differences between healthy subjects and patients with schizophrenia or schizoaffective disorder: A graph and control theoretical perspective. *Front. Psychiatry* 991.
- Dion, M.L., Sumner, J.L., Mitchell, S.M., 2018. Gendered citation patterns across political science and social science methodology fields. *Political Anal.* 26 (3), 312–327.
- Domenech, P., Koehlin, E., 2015. Executive control and decision-making in the prefrontal cortex. *Curr. Opin. Behav. Sci.* 1, 101–106.
- Doran, G.T., 1981. There's a S.M.A.R.T. Way to write management's goals and objectives. *Manag. Rev.* 70 (11), 35–36.
- Dosenbach, N.U., Fair, D.A., Miezin, F.M., Cohen, A.L., Wenger, K.K., Dosenbach, R.A., Fox, M.D., Snyder, A.Z., Vincent, J.L., Raichle, M.E., et al., 2007. Distinct brain networks for adaptive and stable task control in humans. *Proc. Natl. Acad. Sci.* 104 (26), 11073–11078.
- Drucker, P., 1954. *The Practice of Management*. Routledge.
- D'Souza, R.M., Di Bernardo, M., Liu, Y.-Y., 2023. Controlling complex networks with complex nodes. *Nat. Rev. Phys.* 5 (4), 250–262.
- Duckworth, A.L., Gendler, T.S., Gross, J.J., 2016. Situational strategies for self-control. *Perspect. Psychol. Sci.* 11 (1), 35–55.
- Duckworth, A.L., Kern, M.L., 2011. A meta-analysis of the convergent validity of self-control measures. *J. Res. Pers.* 45 (3), 259–268.
- Duckworth, A.L., Milkman, K.L., Laibson, D., 2018. Beyond willpower: Strategies for reducing failures of self-control. *Psychol. Sci. the Public Interes.* 19 (3), 102–129.
- Duckworth, A.L., Peterson, C., Matthews, M.D., Kelly, D.R., 2007. Grit: perseverance and passion for long-term goals. *J. Pers. Soc. Psychol.* 92 (6), 1087.
- Duckworth, A.L., Seligman, M.E., 2005. Self-discipline outdoes IQ in predicting academic performance of adolescents. *Psychol. Sci.* 16 (12), 939–944.
- Duncan, J., 2010. The multiple-demand (MD) system of the primate brain: mental programs for intelligent behaviour. *Trends Cogn. Sci.* 14 (4), 172–179.
- Duncan, J., Emslie, H., Williams, P., Johnson, R., Freer, C., 1996. Intelligence and the frontal lobe: The organization of goal-directed behavior. *Cogn. Psychol.* 30 (3), 257–303.
- Durstewitz, D., Koppe, G., Thurm, M.I., 2023. Reconstructing computational system dynamics from neural data with recurrent neural networks. *Nature Rev. Neurosci.* 24 (11), 693–710.
- Dweck, C.S., 2017. From needs to goals and representations: Foundations for a unified theory of motivation, personality, and development. *Psychol. Rev.* 124 (6), 689.
- Dweck, C.S., Yeager, D.S., 2019. Mindsets: A view from two eras. *Perspect. Psychol. Sci.* 14 (3), 481–496.
- Dworkin, J.D., Linn, K.A., Teich, E.G., Zurn, P., Shinohara, R.T., Bassett, D.S., 2020. The extent and drivers of gender imbalance in neuroscience reference lists. *bioRxiv*.
- Egner, T., 2017. *The Wiley Handbook of Cognitive Control*. John Wiley & Sons.
- Egner, T., Hirsch, J., 2005. Cognitive control mechanisms resolve conflict through cortical amplification of task-relevant information. *Nature Neurosci.* 8 (12), 1784–1790.
- Eisenberg, I.W., Bissett, P.G., Zeynep Enkavi, A., Li, J., MacKinnon, D.P., Marsch, L.A., Poldrack, R.A., 2019. Uncovering the structure of self-regulation through data-driven ontology discovery. *Nat. Commun.* 10 (1), 2319.
- Eisenreich, B.R., Akaishi, R., Hayden, B.Y., 2017. Control without controllers: Toward a distributed neuroscience of executive control. *J. Cogn. Neurosci.* 29 (10), 1684–1698.
- Elias, N., 1939. The civilizing process.
- Emonds, N., Herberg, E., Gerchen, M.F., Pritsch, M., Rocha, J., Zamosc, V., Kirsch, P., Herzog, R., Koppe, G., 2026. A data-driven closed-loop control approach to drive neural state transitions for mechanistic insight. *Hum. Brain Mapp.* 47 (11), e70600, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/hbm.70600.
- Enisman, M., Kleiman, T., 2024. The relative difficulty of resolving motivational conflicts is affective context-dependent. *Emotion*.
- Enkavi, A.Z., Eisenberg, I.W., Bissett, P.G., Mazza, G.L., MacKinnon, D.P., Marsch, L.A., Poldrack, R.A., 2019. Large-scale analysis of test-retest reliabilities of self-regulation measures. *Proc. Natl. Acad. Sci.* 116 (12), 5472–5477.

- Falk, E.B., Bassett, D.S., 2017. Brain and social networks: fundamental building blocks of human experience. *Trends Cogn. Sci.* 21 (9), 674–690.
- Fang, F., Godlewska, B., Cho, R.Y., Savitz, S.I., Selvaraj, S., Zhang, Y., 2022. Personalizing repetitive transcranial magnetic stimulation for precision depression treatment based on functional brain network controllability and optimal control analysis. *NeuroImage* 260, 119465.
- Feather, N.T., 1982. Expectations and Actions: Expectancy-Value Models in Psychology. Routledge.
- Fine, J.M., Hayden, B.Y., 2022. The whole prefrontal cortex is premotor cortex. *Philos. Trans. R. Soc. B* 377 (1844), 20200524.
- Frank, M.J., 2006. Hold your horses: a dynamic computational role for the subthalamic nucleus in decision making. *Neural Netw.* 19 (8), 1120–1136.
- Frank, M.J., Loughry, B., O'Reilly, R.C., 2001. Interactions between frontal cortex and basal ganglia in working memory: a computational model. *Cogn. Affect. & Behav. Neurosci.* 1, 137–160.
- Frese, M., Sabini, J., 2021. Goal Directed Behavior: The Concept of Action in Psychology. Taylor & Francis.
- Freund, M.C., Etzel, J.A., Braver, T.S., 2021. Neural coding of cognitive control: the representational similarity analysis approach. *Trends Cogn. Sci.* 25 (7), 622–638.
- Friedman, J., Hastie, T., Tibshirani, R., 2008. Sparse inverse covariance estimation with the graphical lasso. *Biostatistics* 9 (3), 432–441.
- Friedman, N.P., Miyake, A., 2017. Unity and diversity of executive functions: Individual differences as a window on cognitive structure. *Cortex* 86, 186–204.
- Friedman, N.P., Miyake, A., Corley, R.P., Young, S.E., DeFries, J.C., Hewitt, J.K., 2006. Not all executive functions are related to intelligence. *Psychol. Sci.* 17 (2), 172–179.
- Friedman, N.P., Robbins, T.W., 2022. The role of prefrontal cortex in cognitive control and executive function. *Neuropsychopharmacology* 47 (1), 72–89.
- Fritz, J., Dreisbach, G., 2013. Conflicts as aversive signals: Conflict priming increases negative judgments for neutral stimuli. *Cogn. Affect. & Behav. Neurosci.* 13 (2), 311–317.
- Frömer, R., Dean Wolf, C.K., Shenav, A., 2019. Goal congruency dominates reward value in accounting for behavioral and neural correlates of value-based decision-making. *Nat. Commun.* 10 (1), 4926.
- Fujita, K., 2011. On conceptualizing self-control as more than the effortful inhibition of impulses. *Pers. Soc. Psychol. Rev.* 15 (4), 352–366.
- Fulvio, J.M., Akinola, I., Postle, B.R., 2021. Gender (im)balance in citation practices in cognitive neuroscience. *J. Cogn. Neurosci.* 33 (1), 3–7.
- Funahashi, S., Chafee, M.V., Goldman-Rakic, P.S., 1993. Prefrontal neuronal activity in rhesus monkeys performing a delayed anti-saccade task. *Nature* 365 (6448), 753–756.
- Fuster, J.M., 1990. Prefrontal cortex and the bridging of temporal gaps in the perception-action cycle. *Ann. New York Acad. Sci.* 608, 318–329.
- Fuster, J.M., Alexander, G.E., 1971. Neuron activity related to short-term memory. *Science* 173 (3997), 652–654.
- Gennara, A., Peetz, J., Milyavskaya, M., 2023. When more is less: Self-control strategies are seen as less indicative of self-control than just willpower. *J. Exp. Soc. Psychol.* 106, 104457.
- Gerlach, M., Peixoto, T.P., Altmann, E.G., 2018. A network approach to topic models. *Sci. Adv.* 4 (7), eaq1360.
- Giallanza, T., Campbell, D., Cohen, J.D., Rogers, T.T., 2024. An integrated model of semantics and control. *Psychol. Rev.*
- Glasser, M.F., Coalson, T.S., Robinson, E.C., Hacker, C.D., Harwell, J., Yacoub, E., Ugurbil, K., Andersson, J., Beckmann, C.F., Jenkinson, M., et al., 2016. A multi-modal parcellation of human cerebral cortex. *Nature* 536 (7615), 171–178.
- Glimcher, P.W., Fehr, E., 2013. *Neuroeconomics: Decision Making and the Brain*. Academic Press.
- Goghari, V.M., MacDonald, III, A.W., 2009. The neural basis of cognitive control: response selection and inhibition. *Brain Cogn.* 71 (2), 72–83.
- Goldman-Rakic, P.S., 1987. Circuitry of primate prefrontal cortex and regulation of behavior by representational memory. *Compr. Physiol.* 1987 (1255), 373–417, arXiv: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/j.2040-4603.1987.tb00922.x>.
- Gollwitzer, P.M., 2013. The history of the concept of goals. *A Century Psychol. (Psychology Revivals)* 224–240.
- Gomez-Marin, A., Ghazanfar, A.A., 2019. The life of behavior. *Neuron* 104 (1), 25–36.
- Gratton, G., Cooper, P., Fabiani, M., Carter, C.S., Karayanidis, F., 2018. Dynamics of cognitive control: Theoretical bases, paradigms, and a view for the future. *Psychophysiology* 55 (3), e13016.
- Gratton, C., Laumann, T.O., Gordon, E.M., Adeyemo, B., Petersen, S.E., 2016. Evidence for two independent factors that modify brain networks to meet task goals. *Cell Rep.* 17 (5), 1276–1288.
- Gratton, C., Sun, H., Petersen, S.E., 2018. Control networks and hubs. *Psychophysiology* 55 (3), e13032.
- Gross, J.J., 2015. Emotion regulation: Current status and future prospects. *Psychol. Inq.* 26 (1), 1–26.
- Gu, S., Pasqualetti, F., Cieslak, M., Telesford, Q.K., Yu, A.B., Kahn, A.E., Medaglia, J.D., Vettel, J.M., Miller, M.B., Grafton, S.T., et al., 2015. Controllability of structural brain networks. *Nat. Commun.* 6 (1), 8414.
- Hahn, T., Jamalabadi, H., Emden, D., Goltermann, J., Ernsting, J., Winter, N.R., Fisch, L., Leenings, R., Sarink, K., Holstein, V., et al., 2021. A network control theory approach to longitudinal symptom dynamics in major depressive disorder. arXiv preprint arXiv:2107.10178.
- Hahn, T., Winter, N.R., Ernsting, J., Gruber, M., Mauritz, M.J., Fisch, L., Leenings, R., Sarink, K., Blanke, J., Holstein, V., et al., 2023. Genetic, individual, and familial risk correlates of brain network controllability in major depressive disorder. *Mol. Psychiatry* 28 (3), 1057–1063.
- Hasselmo, M.E., 2005. A model of prefrontal cortical mechanisms for goal-directed behavior. *J. Cogn. Neurosci.* 17 (7), 1115–1129.
- Hazy, T.E., Frank, M.J., O'Reilly, R.C., 2006. Banishing the homunculus: making working memory work. *Neuroscience* 139 (1), 105–118.
- He, X., Caciagli, L., Parkes, L.M., Stiso, J., Karrer, T.M., Kim, J.Z., Lu, Z., Menara, T., Pasqualetti, F., Sperling, M.R., et al., 2021. Pathological and metabolic underpinnings of energetic inefficiency in temporal lobe epilepsy. *bioRxiv*.
- Heatherton, T.F., Wagner, D.D., 2011. Cognitive neuroscience of self-regulation failure. *Trends Cogn. Sci.* 15 (3), 132–139.
- Heckhausen, H., 2018. Historical trends in motivation research. In: *Motivation and Action*. Springer, pp. 15–65.
- Heffner, J., Son, J.-Y., FeldmanHall, O., 2021. Emotion prediction errors guide socially adaptive behaviour. *Nat. Hum. Behav.* 5 (10), 1391–1401.
- Held, L.K., Vermeylen, L., Dignath, D., Notebaert, W., Krebs, R.M., Braem, S., 2024. Reinforcement learning of adaptive control strategies. *Commun. Psychol.* 2 (1), 8.
- Henry, T.R., Fogleman, N.D., Nugiel, T., Cohen, J.R., 2022a. Effect of methylphenidate on functional controllability: a preliminary study in medication-naïve children with ADHD. *Transl. Psychiatry* 12 (1), 518.
- Henry, T.R., Robinaugh, D.J., Fried, E.I., 2022b. On the control of psychological networks. *Psychometrika* 87 (1), 188–213.
- Herd, S.A., Hazy, T.E., Chatham, C.H., Brant, A.M., Friedman, N.P., et al., 2014. A neural network model of individual differences in task switching abilities. *Neuropsychologia* 62, 375–389.
- Herzog, S., Schneek, N., Galfalvy, H., Hwei-Choo, T., Schmidt, M., Michel, C.A., Sublette, M.E., Burke, A., Ochsner, K., Mann, J.J., et al., 2025. A neural signature for reappraisal as an emotion regulation strategy: Relationship to stress-related suicidal ideation and negative affect in major depression. *Biol. Psychiatry: Cogn. Neurosci. Neuroimaging* 10 (1), 94–102.
- Higgins, E.T., 2005. Value from regulatory fit. *Curr. Dir. Psychol. Sci.* 14 (4), 209–213.
- Higgins, E.T., 2011. *Beyond Pleasure and Pain: How Motivation Works*. Oxford University Press.
- Hofmann, W., 2024. Going beyond the individual level in self-control research. *Nat. Rev. Psychol.* 3 (1), 56–66.
- Hofmann, W., Meindl, P., Mooijman, M., Graham, J., 2018. Morality and self-control: How they are intertwined and where they differ. *Curr. Dir. Psychol. Sci.* 27 (4), 286–291.
- Holroyd, C.B., 2025. The controlosphere: The neural origin of cognitive effort. *Psychol. Rev.*
- Holroyd, C.B., Ribas-Fernandes, J.J., Shahnazian, D., Silvetti, M., Verguts, T., 2018. Human midcingulate cortex encodes distributed representations of task progress. *Proc. Natl. Acad. Sci.* 115 (25), 6398–6403.
- Inzlicht, M., Bartholow, B.D., Hirsh, J.B., 2015. Emotional foundations of cognitive control. *Trends Cogn. Sci.* 19 (3), 126–132.
- Inzlicht, M., Berkman, E., 2015. Six questions for the resource model of control (and some answers). *Soc. Pers. Psychol. Compass* 9 (10), 511–524.
- Inzlicht, M., Friese, M., 2019. The past, present, and future of ego depletion. *Soc. Psychol.*
- Inzlicht, M., Werner, K.M., Briskin, J.L., Roberts, B.W., 2021. Integrating models of self-regulation. *Annu. Rev. Psychol.* 72 (1), 319–345.
- Jaffe, P.I., Poldrack, R.A., Schafer, R.J., Bissett, P.G., 2023. Modelling human behaviour in cognitive tasks with latent dynamical systems. *Nat. Hum. Behav.* 1–15.
- Jamadar, S.D., Thienel, R., Karayanidis, F., 2015. Task switching processes. *Brain Mapp.: An Encycl. Ref.* 3, 327–335.
- James, W., 1890. The principles of. *Psychology* 2, 94.
- Jeganathan, J., Perry, A., Bassett, D.S., Roberts, G., Mitchell, P.B., Breakspear, M., 2018. Fronto-limbic dysconnectivity leads to impaired brain network controllability in young people with bipolar disorder and those at high genetic risk. *NeuroImage: Clin.* 19, 71–81.
- Jerde, T.A., Merriam, E.P., Riggall, A.C., Hedges, J.H., Curtis, C.E., 2012. Prioritized space in human frontoparietal cortex. *J. Neurosci.* 32 (48), 17382–17390.
- Karrer, T.M., Kim, J.Z., Stiso, J., Kahn, A.E., Pasqualetti, F., Habel, U., Bassett, D.S., 2020. A practical guide to methodological considerations in the controllability of structural brain networks. *J. Neural Eng.* 17 (2), 026031.
- Kelemen, E., Fenton, A.A., 2016. Coordinating different representations in the hippocampus. *Neurobiol. Learn. Mem.* 129, 50–59.
- Kenett, Y.N., Beaty, R.E., Medaglia, J.D., 2018. A computational network control theory analysis of depression symptoms. *Pers. Neurosci.* 1, e16.
- Kidd, C., Palmeri, H., Aslin, R.N., 2013. Rational snacking: Young children's decision-making on the marshmallow task is moderated by beliefs about environmental reliability. *Cognition* 126 (1), 109–114.
- Kikumoto, A., Bhandari, A., Shibata, K., Badre, D., 2024. A transient high-dimensional geometry affords stable conjunctive subspaces for efficient action selection. *Nat. Commun.* 15 (1), 8513.
- Kikumoto, A., Mayr, U., 2020. Conjunctive representations that integrate stimuli, responses, and rules are critical for action selection. *Proc. Natl. Acad. Sci.* 117 (19), 10603–10608.

- Kim, J.Z., Bassett, D.S., 2020. Linear dynamics and control of brain networks. *Neural Eng.* 497–518.
- Kim, J.Z., Betzel, R.F., Beyh, A., Howell, A., Kuceyeski, A., Larsen, B., Seguin, C., Zhang, X.-H., Holmes, A., Parkes, L., 2025. Inferring macroscopic intrinsic neural timescales using optimal control theory. *Nat Commun.* 16, 11639.
- Kim, J.Z., Soffer, J.M., Kahn, A.E., Vettel, J.M., Pasqualetti, F., Bassett, D.S., 2018. Role of graph architecture in controlling dynamical networks with applications to neural systems. *Nat. Phys.* 14 (1), 91–98.
- Kirk, D.E., 2004. *Optimal Control Theory: An Introduction*. Courier Corporation.
- Koban, L., Gianaros, P.J., Kober, H., Wager, T.D., 2021. The self in context: brain systems linking mental and physical health. *Nature Rev. Neurosci.* 22 (5), 309–322.
- Koechlin, E., Summerfield, C., 2007. An information theoretical approach to prefrontal executive function. *Trends Cogn. Sci.* 11 (6), 229–235.
- Kok, A., 2022. Cognitive control, motivation and fatigue: A cognitive neuroscience perspective. *Brain Cogn.* 160, 105880.
- Kool, W., Botvinick, M., 2018. Mental labour. *Nat. Hum. Behav.* 2 (12), 899–908.
- Kool, W., Shenhav, A., Botvinick, M.M., 2017. Cognitive control as cost-benefit decision making. *Wiley Handb. Cogn. Control.* 167–189.
- Kotabe, H.P., Hofmann, W., 2015. On integrating the components of self-control. *Perspect. Psychol. Sci.* 10 (5), 618–638.
- Kruglanski, A.W., Bélanger, J.J., Chen, X., Köpetz, C., Pierro, A., Mannetti, L., 2012. The energetics of motivated cognition: a force-field analysis. *Psychol Rev* 119 (1), 1.
- Kruglanski, A.W., Chernikova, M., Babush, M., Dugas, M., Schumpe, B.M., 2015. The architecture of goal systems: Multifinality, equifinality, and counterfinality in means—end relations. In: *Advances in Motivation Science*, vol. 2, Elsevier, pp. 69–98.
- Kruglanski, A.W., Kopetz, C., 2009. What Is So Special (And Nonspecial) About Goals?: A View from the Cognitive Perspective. Guilford Press.
- Kruglanski, A.W., Shah, J.Y., Fishbach, A., Friedman, R., Chun, W.Y., Sleeth-Keppel, D., 2018. A theory of goal systems. In: *The Motivated Mind*. Routledge, pp. 207–250.
- Kurzban, R., Duckworth, A., Kable, J.W., Myers, J., 2013. An opportunity cost model of subjective effort and task performance. *Behav. Brain Sci.* 36 (6), 661–679.
- Lee, P.-S., Sewell, D.K., 2024. A revised diffusion model for conflict tasks. *Psychon. Bull. Rev.* 31 (1), 1–31.
- Lee, H.J., Smith, D.M., Hauenstein, C.E., Dworetzky, A., Kraus, B.T., Dorn, M., Nee, D.E., Gratton, C., 2025. Precise individual measures of inhibitory control. *Nat. Hum. Behav.* 1–18.
- Lengyel, M., Dayan, P., 2007. Hippocampal contributions to control: the third way. *Adv. Neural Inf. Process. Syst.* 20.
- Leung, B.K., Chieng, B., Becchi, S., Balleine, B.W., 2024. A ventral pallidal-thalamocortical circuit mediates the cognitive control of instrumental action. *Curr. Biol.* 34 (15), 3315–3326.
- Lewin, K., 1936. *Principles of Topological Psychology*. Read Books Ltd.
- Lieder, F., Shenhav, A., Musslick, S., Griffiths, T.L., 2018. Rational metareasoning and the plasticity of cognitive control. *PLoS Comput. Biol.* 14 (4), e1006043.
- Lim, J., Mitrai, I., Daoitidis, P., Stamoulis, C., 2025. The adolescent functional connectome is dynamically controlled by a sparse core of cognitive and topological hubs. *NeuroImage (ISSN: 1053-8119)* 322, 121562, URL <https://www.sciencedirect.com/science/article/pii/S1053811925005658>.
- Liston, C., Watts, R., Tottenham, N., Davidson, M.C., Niogi, S., Ulug, A.M., Casey, B., 2006. Frontostriatal microstructure modulates efficient recruitment of cognitive control. *Cerebral Cortex* 16 (4), 553–560.
- Liu, Y.-Y., Barabási, A.-L., 2016. Control principles of complex systems. *Rev. Modern Phys.* 88 (3), 035006.
- Liu, Y.-Y., Slotine, J.-J., Barabási, A.-L., 2012. *Control Centrality and Hierarchical Structure in Complex Networks*. Public Library of Science San Francisco, USA.
- Liu, Q., Xiong, H., Shi, W., Di, S., Cheng, X., Liu, N., Luo, N., Zhang, Y., Jiang, T., 2026. Energy inefficiency underpinning brain state dysregulation in individuals with major depressive disorder. *Nat. Ment. Health* 1–16.
- Livnat, A., Pippenger, N., 2006. An optimal brain can be composed of conflicting agents. *Proc. Natl. Acad. Sci.* 103 (9), 3198–3202.
- Lopez, R.B., Hofmann, W., Wagner, D.D., Kelley, W.M., Heatherton, T.F., 2014. Neural predictors of giving in to temptation in daily life. *Psychol. Sci.* 25 (7), 1337–1344.
- Luna, B., 2012. The relevance of immaturities in the juvenile brain to culpability and rehabilitation. *Hast. Law J.* 63 (6), 1469.
- Luna, B., Marek, S., Larsen, B., Tervo-Clemmens, B., Chahal, R., 2015. An integrative model of the maturation of cognitive control. *Annu. Rev. Neurosci.* 38, 151–170.
- Luna, B., Padmanabhan, A., O'Hearn, K., 2010. What has fMRI told us about the development of cognitive control through adolescence? *Brain Cogn.* 72 (1), 101–113.
- Luna, B., Wright, C., 2016. *Adolescent Brain Development: Implications for the Juvenile Criminal Justice System*. American Psychological Association.
- Lundqvist, M., Brincat, S.L., Rose, J., Warden, M.R., Buschman, T.J., Miller, E.K., Herman, P., 2023. Working memory control dynamics follow principles of spatial computing. *Nat. Commun.* 14 (1), 1429.
- Luppi, A.L., Singleton, S.P., Hansen, J.Y., Jamison, K.W., Bzdok, D., Kuceyeski, A., Betzel, R.F., Misisic, B., 2024. Contributions of network structure, chemoarchitecture and diagnostic categories to transitions between cognitive topographies. *Nat. Biomed. Eng.* 8 (9), 1142–1161.
- Lydon, D.M., Wilson, S.J., Child, A., Geier, C.F., 2014. Adolescent brain maturation and smoking: what we know and where we're headed. *Neurosci. Biobehav. Rev.* 45, 323–342.
- Lynn, C.W., Bassett, D.S., 2019. The physics of brain network structure, function and control. *Nat. Rev. Phys.* 1 (5), 318–332.
- MacDonald, A.W., Cohen, J.D., Stenger, V.A., Carter, C.S., 2000. Dissociating the role of the dorsolateral prefrontal and anterior cingulate cortex in cognitive control. *Science* 288 (5472), 1835–1838.
- Mack, M.L., Preston, A.R., Love, B.C., 2020. Ventromedial prefrontal cortex compression during concept learning. *Nat. Commun.* 11 (1), 46.
- Mahadevan, A.S., Cornblath, E.J., Lydon-Staley, D.M., Zhou, D., Parkes, L., Larsen, B., Adebimpe, A., Kahn, A.E., Gur, R.C., Gur, R.E., et al., 2021. Alprazolam modulates persistence energy during emotion processing in first-degree relatives of individuals with schizophrenia: a network control study. *bioRxiv*.
- Maliniak, D., Powers, R., Walter, B.F., 2013. The gender citation gap in international relations. *Int. Organ.* 67 (4), 889–922.
- Mante, V., Sussillo, D., Shenoy, K.V., Newsome, W.T., 2013. Context-dependent computation by recurrent dynamics in prefrontal cortex. *Nature* 503 (7474), 78–84.
- Marek, S., Hwang, K., Foran, W., Hallquist, M.N., Luna, B., 2015. The contribution of network organization and integration to the development of cognitive control. *PLoS Biol.* 13 (12), e1002328.
- Marken, R.S., Mansell, W., 2013. Perceptual control as a unifying concept in psychology. *Rev. Gen. Psychol.* 17 (2), 190–195.
- Marr, D., 1982. *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*. MIT Press.
- McDougle, S.D., Ballard, I.C., Baribault, B., Bishop, S.J., Collins, A.G., 2022. Executive function assigns value to novel goal-congruent outcomes. *Cerebral Cortex* 32 (1), 231–247.
- McGowan, A.L., Sayed, F., Boyd, Z.M., Jovanova, M., Kang, Y., Speer, M.E., Cosme, D., Mucha, P.J., Ochsner, K.N., Bassett, D.S., et al., 2023. Dense sampling approaches for psychiatry research: Combining scanners and smartphones. *Biol. Psychiatry* 93 (8), 681–689.
- McGuire, J.T., Kable, J.W., 2013. Rational temporal predictions can underlie apparent failures to delay gratification. *Psychol Rev* 120 (2), 395.
- McTeague, L.M., Huemer, J., Carreon, D.M., Jiang, Y., Eickhoff, S.B., Etkin, A., 2017. Identification of common neural circuit disruptions in cognitive control across psychiatric disorders. *Am. J. Psychiatry* 174 (7), 676–685.
- Medaglia, J.D., 2019. Clarifying cognitive control and the controllable connectome. *Wiley Interdiscip. Rev.: Cogn. Sci.* 10 (1), e1471.
- Medaglia, J.D., Zurn, P., Sinnott-Armstrong, W., Bassett, D.S., 2017. Mind control as a guide for the mind. *Nat. Hum. Behav.* 1 (6), 0119.
- Medalla, M., Barbas, H., 2009. Synapses with inhibitory neurons differentiate anterior cingulate from dorsolateral prefrontal pathways associated with cognitive control. *Neuron* 61 (4), 609–620.
- Mehrfhof, S.Z., Fleming, H., Nord, C.L., 2025. An interoceptive model of energy allostasis linking metabolic and mental health. *Sci. Adv.* 11 (39), eady4356.
- Menon, V., 2023. 20 years of the default mode network: A review and synthesis. *Neuron* 111 (16), 2469–2487.
- Menon, V., D'Esposito, M., 2022. The role of PFC networks in cognitive control and executive function. *Neuropsychopharmacology* 47 (1), 90–103.
- Menon, V., Uddin, L.Q., 2010. Saliency, switching, attention and control: a network model of insula function. *Brain Struct. Funct.* 214, 655–667.
- Mesulam, M.-M., 1998. From sensation to cognition. *Brain: A J. Neurol.* 121 (6), 1013–1052.
- Miller, E.K., 2000. The prefrontal cortex and cognitive control. *Nature Rev. Neurosci.* 1 (1), 59–65.
- Miller, E.K., Brincat, S.L., Roy, J.E., 2024. Cognition is an emergent property. *Curr. Opin. Behav. Sci.* 57, 101388.
- Miller, P., Brody, C.D., Romo, R., Wang, X.-J., 2003. A recurrent network model of somatosensory parametric working memory in the prefrontal cortex. *Cerebral Cortex* 13 (11), 1208–1218.
- Miller, G.A., Eugene, G., Pribram, K.H., 2017. *Plans and the Structure of Behaviour*. Routledge.
- Miller, G.A., Galanter, E., Pribram, K.H., 1960. *Plans and the Structure of Behavior*. Henry Holt and Co.
- Milyavskaya, M., Berkman, E.T., De Ridder, D.T., 2019. The many faces of self-control: Tacit assumptions and recommendations to deal with them. *Motiv. Sci.* 5 (1), 79.
- Mischel, W., Ayduk, O., Berman, M.G., Casey, B., Gotlib, I.H., Jonides, J., Kross, E., Teslovich, T., Wilson, N.L., Zayas, V., et al., 2011. 'Willpower' over the life span: decomposing self-regulation. *Soc. Cogn. Affect. Neurosci.* 6 (2), 252–256.
- Mischel, W., Ebbsen, E.B., 1970. Attention in delay of gratification. *J. Pers. Soc. Psychol.* 16 (2), 329.
- Mitchell, S.M., Lange, S., Brus, H., 2013. Gendered citation patterns in international relations journals. *Int. Stud. Perspect.* 14 (4), 485–492.
- Miyake, A., Friedman, N.P., 2012. The nature and organization of individual differences in executive functions: Four general conclusions. *Curr. Dir. Psychol. Sci.* 21 (1), 8–14.
- Moffitt, T.E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R.J., Harrington, H., Houts, R., Poulton, R., Roberts, B.W., Ross, S., et al., 2011. A gradient of childhood self-control predicts health, wealth, and public safety. *Proc. Natl. Acad. Sci.* 108 (7), 2693–2698.

- Molinario, G., Collins, A.G., 2023. A goal-centric outlook on learning. *Trends Cogn. Sci.*
- Molnar-Szakacs, I., Uddin, L.Q., 2022. Anterior insula as a gatekeeper of executive control. *Neurosci. Biobehav. Rev.* 139, 104736.
- Moneta, N., Garvert, M.M., Heekeren, H.R., Schuck, N.W., 2023. Task state representations in vmPFC mediate relevant and irrelevant value signals and their behavioral influence. *Nat. Commun.* 14 (1), 3156.
- Monsell, S., 2003. Task switching. *Trends Cogn. Sci.* 7 (3), 134–140.
- Motter, A.E., 2015. Networkcontrolology. *Chaos: An Interdiscip. J. Nonlinear Sci.* 25 (9).
- Muldoon, S.F., Pasqualetti, F., Gu, S., Cieslak, M., Grafton, S.T., Vettel, J.M., Bassett, D.S., 2016. Stimulation-based control of dynamic brain networks. *PLoS Comput. Biol.* 12 (9), e1005076.
- Muller, L., Chavane, F., Reynolds, J., Sejnowski, T.J., 2018. Cortical travelling waves: mechanisms and computational principles. *Nature Rev. Neurosci.* 19 (5), 255–268.
- Müller, U., Kerns, K., 2015. The development of executive function. In: *Handbook of Child Psychology and Developmental Science: Cognitive Processes*, vol. 2, pp. 571–623.
- Munakata, Y., Herd, S.A., Chatham, C.H., Depue, B.E., Banich, M.T., O'Reilly, R.C., 2011. A unified framework for inhibitory control. *Trends Cogn. Sci.* 15 (10), 453–459.
- Munakata, Y., Michaelson, L.E., 2021. Executive functions in social context: Implications for conceptualizing, measuring, and supporting developmental trajectories. *Annu. Rev. Dev. Psychol.* 3 (1), 139–163.
- Munakata, Y., Snyder, H.R., Chatham, C.H., 2012. Developing cognitive control: Three key transitions. *Curr. Dir. Psychol. Sci.* 21 (2), 71–77.
- Musall, S., Urai, A.E., Sussillo, D., Churchland, A.K., 2019. Harnessing behavioral diversity to understand neural computations for cognition. *Curr. Opin. Neurobiol.* 58, 229–238.
- Musslick, S., Bizyaeva, A., 2024. Examining cognitive flexibility and stability through the lens of dynamical systems. *Curr. Opin. Behav. Sci.* 57, 101375.
- Musslick, S., Cohen, J.D., 2021. Rationalizing constraints on the capacity for cognitive control. *Trends Cogn. Sci.* 25 (9), 757–775.
- Narayanan, N.S., Cavanagh, J.F., Frank, M.J., Laubach, M., 2013. Common medial frontal mechanisms of adaptive control in humans and rodents. *Nature Neurosci.* 16 (12), 1888–1895.
- Neal, D.T., Wood, W., Drolet, A., 2013. How do people adhere to goals when willpower is low? The profits (and pitfalls) of strong habits. *J. Pers. Soc. Psychol.* 104 (6), 959.
- Nee, D.E., Jonides, J., 2008. Dissociable interference-control processes in perception and memory. *Psychol. Sci.* 19 (5), 490–500.
- Nee, D.E., Wager, T.D., Jonides, J., 2007. Interference resolution: insights from a meta-analysis of neuroimaging tasks. *Cogn. Affect. & Behav. Neurosci.* 7 (1), 1–17.
- Niendam, T.A., Laird, A.R., Ray, K.L., Dean, Y.M., Glahn, D.C., Carter, C.S., 2012. Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cogn. Affect. & Behav. Neurosci.* 12, 241–268.
- Nigg, J.T., 2017. Annual Research Review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology. *J. Child Psychol. Psychiatry* 58 (4), 361–383.
- Noble, S., Curtiss, J., Pessoa, L., Scheinost, D., 2023. The tip of the iceberg: a call to embrace anti-localizationism in human neuroscience research.
- Noudoost, B., Chang, M.H., Steinmetz, N.A., Moore, T., 2010. Top-down control of visual attention. *Curr. Opin. Neurobiol.* 20 (2), 183–190.
- Nozari, E., Stiso, J., Caciagli, L., Cornblath, E.J., He, X., Bertolero, M.A., Mahadevan, A.S., Pappas, G.J., Bassett, D.S., 2020. Is the brain macroscopically linear? A system identification of resting state dynamics. *bioRxiv*.
- Ochsner, K.N., Gross, J.J., 2005. The cognitive control of emotion. *Trends Cogn. Sci.* 9 (5), 242–249.
- Ochsner, K.N., Gross, J.J., 2014. *The Neural Bases of Emotion and Emotion Regulation: A Valuation Perspective*. The Guilford Press.
- Ochsner, K.N., Silvers, J.A., Buhle, J.T., 2012. Functional imaging studies of emotion regulation: a synthetic review and evolving model of the cognitive control of emotion. *Ann. New York Acad. Sci.* 1251 (1), E1–E24.
- O'Neill, J., 1986. The disciplinary society: from Weber to Foucault. *Br. J. Sociol.* 42–60.
- O'Reilly, R.C., Frank, M.J., 2006. Making working memory work: a computational model of learning in the prefrontal cortex and basal ganglia. *Neural Comput.* 18 (2), 283–328.
- O'Reilly, R.C., Hazy, T.E., Herd, S.A., 2016. The leabra cognitive architecture: How to play 20 principles with nature. *Oxf. Handb. Cogn. Sci.* 91, 91–116.
- Otto, A.R., Westbrook, A., Daunizeau, J., 2025. Why is cognitive effort experienced as costly? *Trends Cogn. Sci.*
- Oyserman, D., Lewis, Jr., N.A., Yan, V.X., Fisher, O., O'Donnell, S.C., Horowitz, E., 2017. An identity-based motivation framework for self-regulation. *Psychol. Inq.* 28 (2–3), 139–147.
- Padmala, S., Pessoa, L., 2011. Reward reduces conflict by enhancing attentional control and biasing visual cortical processing. *J. Cogn. Neurosci.* 23 (11), 3419–3432.
- Park, N., Peterson, C., Seligman, M.E., 2004. Strengths of character and well-being. *J. Soc. Clin. Psychol.* 23 (5), 603–619.
- Park, D.C., Reuter-Lorenz, P., 2009. The adaptive brain: aging and neurocognitive scaffolding. *Annu. Rev. Psychol.* 60, 173–196.
- Park, E.H., Sparks, K.C.O., Grubbs, G., Taborga, D., Nicholas, K., Ahmed, A.S., Ruiz-Pérez, N., Kim, N., Segura-Carrillo, S., Fenton, A.A., 2025. Cognitive control of behavior and hippocampal information processing without medial prefrontal cortex. *ELife* 13.
- Parke, L., Kim, J.Z., Stiso, J., Brynildsen, J.K., Cieslak, M., Covitz, S., Gur, R.E., Gur, R.C., Pasqualetti, F., Shinohara, R.T., et al., 2024. Using network control theory to study the dynamics of the structural connectome. *Nat. Protoc.* 19, 3721–3749.
- Parke, L., Kim, J.Z., Stiso, J., Calkins, M.E., Cieslak, M., Gur, R.E., Gur, R.C., Moore, T.M., Ouellet, M., Roalf, D.R., et al., 2022. Asymmetric signaling across the hierarchy of cytoarchitecture within the human connectome. *Sci. Adv.* 8 (50), eadd2185.
- Parke, L., Moore, T.M., Calkins, M.E., Cieslak, M., Roalf, D.R., Wolf, D.H., Gur, R.C., Gur, R.E., Satterthwaite, T.D., Bassett, D.S., 2021. Network controllability in transmodal cortex predicts positive psychosis spectrum symptoms. *Biol. Psychiatry* 90 (6), 409–418.
- Parvizi, J., Rangarajan, V., Shirer, W.R., Desai, N., Greicius, M.D., 2013. The will to persevere induced by electrical stimulation of the human cingulate gyrus. *Neuron* 80 (6), 1359–1367.
- Patankar, S.P., Kim, J.Z., Pasqualetti, F., Bassett, D.S., 2020. Path-dependent connectivity, not modularity, consistently predicts controllability of structural brain networks. *Netw. Neurosci.* 4 (4), 1091–1121.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al., 2011. Scikit-learn: Machine learning in Python. *J. Mach. Learn. Res.* 12, 2825–2830.
- Peixoto, T.P., 2014. The graph-tool python library. *Figshare*.
- Pessoa, L., 2009. How do emotion and motivation direct executive control? *Trends Cogn. Sci.* 13 (4), 160–166.
- Pessoa, L., 2017. Cognitive control and emotional processing. *Wiley Handb. Cogn. Control*. 392–407.
- Pessoa, L., 2023. The entangled brain. *J. Cogn. Neurosci.* 35 (3), 349–360.
- Pinker, S., 2012. *The Better Angels of Our Nature: Why Violence Has Declined*. Penguin books.
- Pistilli, G., Leidinger, A., Jernite, Y., Kasirzadeh, A., Luccioni, A.S., Mitchell, M., 2024. Civics: Building a dataset for examining culturally-informed values in large language models. In: *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, vol. 7, pp. 1132–1144.
- Plato, P., 1952. *Phaedrus*, vol. 1, Bobbs-Merrill Indianapolis.
- Poldrack, R.A., Sabb, F.W., Foerster, K., Tom, S.M., Asarnow, R.F., Bookheimer, S.Y., Knowlton, B.J., 2005. The neural correlates of motor skill automaticity. *J. Neurosci.* 25 (22), 5356–5364.
- Powers, W.T., Powers, W.T., 1973. *Behavior: The Control of Perception*. Aldine Chicago.
- Prystawski, B., Mohnert, F., Tošić, M., Lieder, F., 2022. Resource-rational models of human goal pursuit. *Top. Cogn. Sci.* 14 (3), 528–549.
- Randles, D., Harlow, I., Inzlicht, M., 2017. A pre-registered naturalistic observation of within domain mental fatigue and domain-general depletion of self-control. *PLoS One* 12 (9), e0182980.
- Read, D., Loewenstein, G., Kalyanaraman, S., 1999. Mixing virtue and vice: Combining the immediacy effect and the diversification heuristic. *J. Behav. Decis. Mak.* 12 (4), 257–273.
- Reuter-Lorenz, P.A., Park, D.C., 2014. How does it STAC up? Revisiting the scaffolding theory of aging and cognition. *Neuropsychol. Rev.* 24 (3), 355–370.
- Ribot, T., 1911. *Voluntary Attention*. Open Court Publishing Co.
- Rieck, J., Wrobel, J., Porras, A.R., McRae, K., Gowin, J.L., 2024. Neural signatures of emotion regulation. *Sci. Rep.* 14 (1), 1775.
- Ritz, H., Leng, X., Shenav, A., 2022. Cognitive control as a multivariate optimization problem. *J. Cogn. Neurosci.* 34 (4), 569–591.
- Ritz, H., Shenav, A., 2024. Orthogonal neural encoding of targets and distractors supports multivariate cognitive control. *Nat. Hum. Behav.* 8 (5), 945–961.
- Rmus, M., McDougale, S.D., Collins, A.G., 2021. The role of executive function in shaping reinforcement learning. *Curr. Opin. Behav. Sci.* 38, 66–73.
- Robson, D.A., Allen, M.S., Howard, S.J., 2020. Self-regulation in childhood as a predictor of future outcomes: A meta-analytic review. *Psychol. Bull.* 146 (4), 324.
- Romer, A.L., Hari, A.R., Strauman, T.J., 2021. Regulatory focus and the p factor: Evidence for self-regulatory dysfunction as a transdiagnostic feature of general psychopathology. *J. Psychiatr. Res.* 137, 178–185.
- Ross, L.N., 2025. Explanation in biology. *Elem. Philosophy Biol.*
- Rotter, J.B., 1966. Generalized expectancies for internal versus external control of reinforcement. *Psychol. Monogr.: Gen. Appl.* 80 (1), 1.
- Rougier, N.P., Noelle, D.C., Braver, T.S., Cohen, J.D., O'Reilly, R.C., 2005. Prefrontal cortex and flexible cognitive control: Rules without symbols. *Proc. Natl. Acad. Sci.* 102 (20), 7338–7343.
- Rouse, T.C., Ni, A.M., Huang, C., Cohen, M.R., 2023. Topological insights into the neural basis of flexible behavior. *Proc. Natl. Acad. Sci.* 120 (24), e2219557120.
- Rubinov, M., 2022. Circular and Unified Analysis in Network Neuroscience. *OSF Preprints*.
- Ryan, R.M., Deci, E.L., Grolnick, W.S., 1995. *Autonomy, Relatedness, and the Self: Their Relation to Development and Psychopathology*. John Wiley & Sons.
- Ryan, R.M., Deci, E.L., et al., 2002. Overview of self-determination theory: An organismic dialectical perspective. *Handb. Self-Determination Res.* 2 (3–33), 36.

- Saberi, M., Rieck, J.R., Golafshan, S., Grady, C.L., Masic, B., Dunkley, B.T., Khatibi, A., 2024. The brain selectively allocates energy to functional brain networks under cognitive control. *Sci. Rep.* 14 (1), 32032.
- Sadaghiani, S., D'Esposito, M., 2015. Functional characterization of the cingulo-opercular network in the maintenance of tonic alertness. *Cerebral Cortex* 25 (9), 2763–2773.
- Salzman, C.D., Fusi, S., 2010. Emotion, cognition, and mental state representation in amygdala and prefrontal cortex. *Annu. Rev. Neurosci.* 33 (1), 173–202.
- Satpute, A.B., Ochsner, K.N., Badre, D., 2012. The neuroscience of goal-directed behavior. In: *Goal-Directed Behavior*. Psychology Press, pp. 49–84.
- Scheid, B.H., Ashourvan, A., Stiso, J., Davis, K.A., Mikhail, F., Pasqualetti, F., Litt, B., Bassett, D.S., 2021. Time-evolving controllability of effective connectivity networks during seizure progression. *Proc. Natl. Acad. Sci.* 118 (5), e2006436118.
- Schiller, D., Levy, I., Niv, Y., LeDoux, J.E., Phelps, E.A., 2008. From fear to safety and back: reversal of fear in the human brain. *J. Neurosci.* 28 (45), 11517–11525.
- Schneek, N., Herzog, S., Lu, J., Yttredahl, A., Ogden, R.T., Galfalvy, H., Burke, A., Stanley, B., Mann, J.J., Ochsner, K.N., 2023. The temporal dynamics of emotion regulation in subjects with major depression and healthy control subjects. *Biol. Psychiatry* 93 (3), 260–267.
- Schuck, N.W., Cai, M.B., Wilson, R.C., Niv, Y., 2016. Human orbitofrontal cortex represents a cognitive map of state space. *Neuron* 91 (6), 1402–1412.
- Schurr, R., Reznik, D., Hillman, H., Bhui, R., Gershman, S.J., 2024. Dynamic computational phenotyping of human cognition. *Nat. Hum. Behav.* 8 (5), 917–931.
- Seeley, W.W., Menon, V., Schatzberg, A.F., Keller, J., Glover, G.H., Kenna, H., Reiss, A.L., Greicius, M.D., 2007. Dissociable intrinsic connectivity networks for salience processing and executive control. *J. Neurosci.* 27 (9), 2349–2356.
- Seguin, C., Sporns, O., Zalesky, A., 2023. Brain network communication: concepts, models and applications. *Nature Rev. Neurosci.* 24 (9), 557–574.
- Sennesh, E., Theriault, J., Brooks, D., van de Meent, J.-W., Barrett, L.F., Quigley, K.S., 2022. Interception as modeling, allostasis as control. *Biol. Psychol.* 167, 108242.
- Shackman, A.J., Salomons, T.V., Slagter, H.A., Fox, A.S., Winter, J.J., Davidson, R.J., 2011. The integration of negative affect, pain and cognitive control in the cingulate cortex. *Nature Rev. Neurosci.* 12 (3), 154–167.
- Shadmehr, R., Huang, H.J., Ahmed, A.A., 2016. Effort, reward, and vigor in decision-making and motor control. *Curr. Biol.: CB* 26 (14), 1929.
- Shah, J., Higgins, E.T., 1997. Expectancy × value effects: Regulatory focus as determinant of magnitude and direction. *J. Pers. Soc. Psychol.* 73 (3), 447.
- Shenhav, A., 2024. The affective gradient hypothesis: an affect-centered account of motivated behavior. *Trends Cogn. Sci.*
- Shenhav, A., Botvinick, M.M., Cohen, J.D., 2013. The expected value of control: an integrative theory of anterior cingulate cortex function. *Neuron* 79 (2), 217–240.
- Shenhav, A., Cohen, J.D., Botvinick, M.M., 2016. Dorsal anterior cingulate cortex and the value of control. *Nature Neurosci.* 19 (10), 1286–1291.
- Shenoy, K.V., Kao, J.C., 2021. Measurement, manipulation and modeling of brain-wide neural population dynamics. *Nat. Commun.* 12 (1), 633.
- Shine, J.M., Breakspear, M., Bell, P.T., Ehgoetz Martens, K.A., Shine, R., Koyejo, O., Sporns, O., Poldrack, R.A., 2019. Human cognition involves the dynamic integration of neural activity and neuromodulatory systems. *Nature Neurosci.* 22 (2), 289–296.
- Silvestrini, N., Musslick, S., Berry, A.S., Vassena, E., 2023. An integrative effort: Bridging motivational intensity theory and recent neurocomputational and neuronal models of effort and control allocation. *Psychol. Rev.* 130 (4), 1081.
- Simon, H.A., 2013. *Administrative Behavior*. Simon and Schuster.
- Singleton, S.P., Luppi, A.H., Carhart-Harris, R.L., Cruzat, J., Roseman, L., Deco, G., Kringelbach, M.L., Stamatakis, E.A., Kuceyeski, A., 2021. LSD flattens the brain's energy landscape: evidence from receptor-informed network control theory. *bioRxiv*.
- Smithers, L.G., Sawyer, A.C., Chittleborough, C.R., Davies, N.M., Davey Smith, G., Lynch, J.W., 2018. A systematic review and meta-analysis of effects of early life non-cognitive skills on academic, psychosocial, cognitive and health outcomes. *Nat. Hum. Behav.* 2 (11), 867–880.
- Somerville, L.H., Casey, B., 2010. Developmental neurobiology of cognitive control and motivational systems. *Curr. Opin. Neurobiol.* 20 (2), 236–241.
- Song, H.F., Yang, G.R., Wang, X.-J., 2016. Training excitatory-inhibitory recurrent neural networks for cognitive tasks: a simple and flexible framework. *PLoS Comput. Biol.* 12 (2), e1004792.
- Sood, G., Laohaprapanon, S., 2018. Predicting race and ethnicity from the sequence of characters in a name. *arXiv preprint arXiv:1805.02109*.
- Speer, S.P., Smids, A., Boksem, M.A., 2022. Cognitive control and dishonesty. *Trends Cogn. Sci.* 26 (9), 796–808.
- Spreng, R.N., DuPre, E., Selarka, D., Garcia, J., Gojkovic, S., Mildner, J., Luh, W.-M., Turner, G.R., 2014. Goal-congruent default network activity facilitates cognitive control. *J. Neurosci.* 34 (42), 14108–14114.
- Spreng, R.N., Grady, C.L., 2010. Patterns of brain activity supporting autobiographical memory, prospection, and theory of mind, and their relationship to the default mode network. *J. Cogn. Neurosci.* 22 (6), 1112–1123.
- Srivastava, P., Fotiadis, P., Parkes, L., Bassett, D.S., 2022. The expanding horizons of network neuroscience: From description to prediction and control. *Neuroimage* 258, 119250.
- Srivastava, P., Mucha, P.J., Falk, E., Pasqualetti, F., Bassett, D.S., 2021. Structural underpinnings of control in multiplex networks. *arXiv preprint arXiv:2103.08757*.
- Srivastava, P., Nozari, E., Kim, J.Z., Ju, H., Zhou, D., Becker, C., Pasqualetti, F., Pappas, G.J., Bassett, D.S., 2020. Models of communication and control for brain networks: distinctions, convergence, and future outlook. *Netw. Neurosci.* 4 (4), 1122–1159.
- Stalnaker, T.A., 2024. Neuroscience: A bottom-up mechanism for cognitive control? *Curr. Biol.* 34 (15), R744–R746.
- Stanovich, K.E., 2020. Why humans are cognitive misers and what it means for the great rationality debate. In: *Routledge Handbook of Bounded Rationality*. Routledge, pp. 196–206.
- Sterling, P., 2012. Allostasis: a model of predictive regulation. *Physiol. Behav.* 106 (1), 5–15.
- Sterling, P., Laughlin, S., 2015. *Principles of Neural Design*. MIT Press.
- Stiso, J., Khambhati, A.N., Menara, T., Kahn, A.E., Stein, J.M., Das, S.R., Gorniak, R., Tracy, J., Litt, B., Davis, K.A., et al., 2019. White matter network architecture guides direct electrical stimulation through optimal state transitions. *Cell Rep.* 28 (10), 2554–2566.
- Stocker, J.E., Koppe, G., Reich, H., Heshmati, S., Kittel-Schneider, S., Hofmann, S.G., Hahn, T., van der Maas, H.L., Waldorp, L., Jamalabadi, H., 2023. Formalizing psychological interventions through network control theory. *Sci. Rep.* 13 (1), 13830.
- Stokes, M.G., Kusunoki, M., Sigala, N., Nili, H., Gaffan, D., Duncan, J., 2013. Dynamic coding for cognitive control in prefrontal cortex. *Neuron* 78 (2), 364–375.
- Suárez, L.E., Mihalik, A., Milisav, F., Marshall, K., Li, M., Vértés, P.E., Lajoie, G., Masic, B., 2024. Connectome-based reservoir computing with the conn2res toolbox. *Nat. Commun.* 15 (1), 656.
- Sutlief, E., Walters, C., Marton, T., Shuler, M.G.H., 2025. The value of initiating a pursuit in temporal decision-making. *Elife* 13, RP99957.
- Szymula, K.P., Pasqualetti, F., Graybiel, A.M., Desrochers, T.M., Bassett, D.S., 2020. Habit learning supported by efficiently controlled network dynamics in naive macaque monkeys. *arXiv vol. 2006*, no. 14565.
- Tamir, D., Corbani, F., Mildner, J., Bassett, D.S., 2025. Tracking the dynamics of the stream of thought reveals its function. *Technol. Mind, Behav.*
- Tang, E., Bassett, D.S., 2018. Colloquium: Control of dynamics in brain networks. *Rev. Modern Phys.* 90 (3), 031003.
- Tang, E., Giusti, C., Baum, G.L., Gu, S., Pollock, E., Kahn, A.E., Roalf, D.R., Moore, T.M., Ruparel, K., Gur, R.C., et al., 2017. Developmental increases in white matter network controllability support a growing diversity of brain dynamics. *Nat. Commun.* 8 (1), 1252.
- Taylor, F.W., 1919. *The Principles of Scientific Management*. Harper & brothers.
- Thayer, J.F., Hansen, A.L., Saus-Rose, E., Johnsen, B.H., 2009. Heart rate variability, prefrontal neural function, and cognitive performance: the neurovisceral integration perspective on self-regulation, adaptation, and health. *Ann. Behav. Med.* 37 (2), 141–153.
- Theriault, J.E., Katsumi, Y., Reimann, H.M., Zhang, J., Deming, P., Dickerson, B.C., Quigley, K.S., Barrett, L.F., 2025. It's not the thought that counts: Allostasis at the core of brain function. *Neuron*.
- Thomson, K.S., Oppenheimer, D.M., 2022. The “effort elephant” in the room: What is effort, anyway? *Perspect. Psychol. Sci.* 17 (6), 1633–1652.
- Todorov, E., Jordan, M.L., 2002. Optimal feedback control as a theory of motor coordination. *Nature Neurosci.* 5 (11), 1226–1235.
- Tolman, E.C., 1948. Cognitive maps in rats and men. *Psychol. Rev.* 55 (4), 189.
- Tolman, E.C., 1951. *Purposive Behavior in Animals and Men*. Univ of California Press.
- Touroutoglou, A., Andreano, J., Dickerson, B.C., Barrett, L.F., 2020. The tenacious brain: How the anterior mid-cingulate contributes to achieving goals. *Cortex* 123, 12–29.
- Towlson, E.K., Vértés, P.E., Yan, G., Chew, Y.L., Walker, D.S., Schafer, W.R., Barabási, A.-L., 2018. Caenorhabditis elegans and the network control framework—FAQs. *Phil. Trans. R. Soc. B* 373 (1758), 20170372.
- Tuleya, L.G.E., 2007. *Thesaurus of Psychological Index Terms*. American Psychological Association.
- Uddin, L.Q., 2021. Cognitive and behavioural flexibility: neural mechanisms and clinical considerations. *Nature Rev. Neurosci.* 22 (3), 167–179.
- Van Den Heuvel, M.P., Kahn, R.S., Goñi, J., Sporns, O., 2012. High-cost, high-capacity backbone for global brain communication. *Proc. Natl. Acad. Sci.* 109 (28), 11372–11377.
- van Ede, F., Board, A.G., Nobre, A.C., 2020. Goal-directed and stimulus-driven selection of internal representations. *Proc. Natl. Acad. Sci.* 117 (39), 24590–24598.
- VandenBos, G.R., 2007. *APA Dictionary of Psychology*. American Psychological Association.
- VandenBos, G.R., 2009. *APA College Dictionary of Psychology*. American Psychological Association.
- Wang, X., Dworkin, J.D., Zhou, D., Stiso, J., Falk, E.B., Bassett, D.S., Zurn, P., Lydon-Staley, D.M., 2021. Gendered citation practices in the field of communication. *Ann. Int. Commun. Assoc.*
- Wang, X.-J., Tegnér, J., Constantinidis, C., Goldman-Rakic, P.S., 2004. Division of labor among distinct subtypes of inhibitory neurons in a cortical microcircuit of working memory. *Proc. Natl. Acad. Sci.* 101 (5), 1368–1373.
- Wang, B., Zhang, S., Yu, X., Niu, Y., Niu, J., Li, D., Zhang, S., Xiang, J., Yan, T., Yang, J., et al., 2022. Alterations in white matter network dynamics in patients with schizophrenia and bipolar disorder. *Hum. Brain Mapp.* 43 (13), 3909–3922.

- Weninger, L., Srivastava, P., Zhou, D., Kim, J.Z., Cornblath, E.J., Bertolero, M.A., Habel, U., Merhof, D., Bassett, D.S., 2022. Information content of brain states is explained by structural constraints on state energetics. *Phys. Rev. E* 106 (1), 014401.
- Wente, A., Zhao, X., Gopnik, A., Kang, C., Kushnir, T., 2020. The developmental and cultural origins of our beliefs about self-control. *Surround. Self-Control*.
- Werner, K.M., Berkman, E.T., 2024. Motivational dynamics of self-control. *Curr. Opin. Psychol.* 59, 101859.
- Westbrook, A., Braver, T.S., 2015. Cognitive effort: A neuroeconomic approach. *Cogn. Affect. & Behav. Neurosci.* 15, 395–415.
- Westbrook, A., Van Den Bosch, R., Määttä, J., Hofmans, L., Papadopetraki, D., Cools, R., Frank, M., 2020. Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work. *Science* 367 (6484), 1362–1366.
- White, R.W., 1959. Motivation reconsidered: the concept of competence. *Psychol. Rev.* 66 (5), 297.
- Widge, A., Zorowitz, S., Basu, I., Paulk, A., Cash, S., Eskandar, E., Deckersbach, T., Miller, E., Dougherty, D., 2019. Deep brain stimulation of the internal capsule enhances human cognitive control and prefrontal cortex function. *Nat. Commun.* 10 (1), 1536.
- Wiener, N., 2019. *Cybernetics or Control and Communication in the Animal and the Machine*. MIT Press.
- Wilmskoetter, J., He, X., Caciagli, L., Jensen, J.H., Marebwa, B., Davis, K.A., Fridriksson, J., Basilakos, A., Johnson, L.P., Rorden, C., et al., 2022. Language recovery after brain injury: A structural network control theory study. *J. Neurosci.* 42 (4), 657–669.
- Wilson, R.C., Takahashi, Y.K., Schoenbaum, G., Niv, Y., 2014. Orbitofrontal cortex as a cognitive map of task space. *Neuron* 81 (2), 267–279.
- Wood, W., Mazar, A., Neal, D.T., 2022. Habits and goals in human behavior: Separate but interacting systems. *Perspect. Psychol. Sci.* 17 (2), 590–605.
- Wu, T., Wang, X., Wu, Q., Spagna, A., Yang, J., Yuan, C., Wu, Y., Gao, Z., Hof, P.R., Fan, J., 2019. Anterior insular cortex is a bottleneck of cognitive control. *NeuroImage* 195, 490–504.
- Wulff, D.U., Mata, R., 2025. Semantic embeddings reveal and address taxonomic incommensurability in psychological measurement. *Nat. Hum. Behav.* 1–11.
- Yan, G., Vértés, P.E., Towilson, E.K., Chew, Y.L., Walker, D.S., Schafer, W.R., Barabási, A.-L., 2017. Network control principles predict neuron function in the *Caenorhabditis elegans* connectome. *Nature* 550 (7677), 519–523.
- Yang, G.R., Joglekar, M.R., Song, H.F., Newsome, W.T., Wang, X.-J., 2019. Task representations in neural networks trained to perform many cognitive tasks. *Nature Neurosci.* 22 (2), 297–306.
- Yarkoni, T., Poldrack, R.A., Nichols, T.E., Van Essen, D.C., Wager, T.D., 2011. Large-scale automated synthesis of human functional neuroimaging data. *Nature Methods* 8 (8), 665–670.
- Yee, D.M., Braver, T.S., 2018. Interactions of motivation and cognitive control. *Curr. Opin. Behav. Sci.* 19, 83–90.
- Yee, D.M., Braver, T.S., 2020. Computational models of cognitive control: past and current approaches. In: Seriès, P. (Ed.), *Computational Psychiatry: A Primer*. MIT Press, Cambridge, MA, pp. 83–104.
- Yee, D.M., Braver, T.S., 2023. Neurocomputational models of cognitive control. In: Sun, R. (Ed.), *The Cambridge Handbook of Computational Cognitive Sciences*. In: *Cambridge Handbooks in Psychology*, Cambridge University Press, Cambridge, pp. 664–702.
- Zacks, J.M., 2020. Event perception and memory. *Annu. Rev. Psychol.* 71 (1), 165–191.
- Zelazo, P.D., Carlson, S.M., 2012. Hot and cool executive function in childhood and adolescence: Development and plasticity. *Child Dev. Perspect.* 6 (4), 354–360.
- Zhang, J., Chen, D., Deming, P., Srirangarajan, T., Theriault, J.E., Kragel, P.A., Hartley, L., Lee, K.M., McVeigh, K., Wager, T.D., et al., 2025. Cortical and subcortical mapping of the human allostatic-interoceptive system using 7 Tesla fMRI. *Nature Neurosci.* 1–12.
- Zhou, D., Ahn, J., Lydon-Staley, D.M., Falk, E.B., Bassett, D.S., Ruscio, A.M., 2025. Neural dynamics underlying the persistence of perseverative thought in depression and anxiety. *bioRxiv* arXiv:https://www.biorxiv.org/content/early/2025/07/29/2025.07.21.666019.full.pdf.
- Zhou, D., Cornblath, E.J., Stiso, J., Teich, E.G., Dworkin, J.D., Blevins, A.S., Bassett, D.S., 2020. Gender Diversity Statement and Code Notebook v1.0. Zenodo.
- Zhou, D., Kang, Y., Cosme, D., Jovanova, M., He, X., Mahadevan, A., Ahn, J., Stanoi, O., Brynildsen, J.K., Cooper, N., et al., 2023a. Mindful attention promotes control of brain network dynamics for self-regulation and discontinues the past from the present. *Proc. Natl. Acad. Sci.* 120 (2), e2201074119.
- Zhou, D., Kim, J.Z., Pines, A.R., Sydnor, V.J., Roalf, D.R., Detre, J., Gur, R.C., Gur, R.E., Satterthwaite, T., Bassett, D., 2022a. Compression supports low-dimensional representations of behavior across neural circuits. In: *NeurIPS 2022 Workshop on Information-Theoretic Principles in Cognitive Systems*. <https://openreview.net/forum?id=eGOWHLUFfpd>.
- Zhou, D., Lynn, C.W., Cui, Z., Ciric, R., Baum, G.L., Moore, T.M., Roalf, D.R., Detre, J.A., Gur, R.C., Gur, R.E., et al., 2022b. Efficient coding in the economics of human brain connectomics. *Netw. Neurosci.* 6 (1), 234–274.
- Zhou, D., Tseytlin, I., Satterthwaite, T., Bassett, D.S., 2023b. Predictive coding from compression, control, and recurrence in human brain networks. In: *2023 Conference on Cognitive Computational Neuroscience*.
- Zöller, D., Sandini, C., Schaer, M., Eliez, S., Bassett, D.S., Van De Ville, D., 2021. Structural control energy of resting-state functional brain states reveals less cost-effective brain dynamics in psychosis vulnerability. *Hum. Brain Mapp.* 42 (7), 2181–2200.